APPLICATIONS OF PUBLIC HEALTH METHODS TO TRANSPORTATION PERFORMANCE MEASUREMENT AND POLICY EVALUATION

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Applications of Public Health methods to transportation performance measurement and policy evaluation

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SUMMARY

Traffic crashes are a substantial public health problem. Globally, more than 1 million people are killed in road traffic crashes (Ameratunga et al. 2006). In the United States, around 35,000 are killed on roadways and an estimated 3 million people are injured (National Center for Statistics and Analysis 2020). Traffic crashes are thus the leading cause of death amongst young people between the ages of 5 and 29 years old in the United States.

Although the injuries and deaths that result from crashes present a significant public health problem, few transportation professionals are trained in public health and are rarely exposed to the frameworks and philosophies that underlie it. The intersection of transportation and health is increasingly of interest to civil engineers, city planners, and public health practitioners. Concerted efforts by governmental, academic, and professional organizations have highlighted the transportation sectors influence on health. Beyond injuries, the transportation sector influences mental health and wellbeing, one's propensity to be physically active, access to healthy diets, medical care, and exposure to infectious diseases (Widener and Hatzopoulou 2016). Understanding how transportation influences health outcomes is important, but there are few efforts to incorporate public health methods into transportation practice. In this dissertation, we propose "The Safe Systems Pyramid" as a means of evaluating transportation safety policies and interventions. The Safe Systems Pyramid is based on the science of injury prevention and control and risk management. Currently, most transportation safety professionals rely on the three "E's" framework, which is outdated, and not scientifically based. The Safe Systems Pyramid can help transportation professionals prioritize projects for safety and communicate their priorities with the public.

In addition to developing a framework for transportation safety and public health, we analyzed a new data source and developed a performance metric for assessing transportation safety. Public health practitioners monitor both health outcomes and risk factors for those outcomes to prevent adverse health events. This research uses vehicle-based speed data and crash injury reports to assess safety on road networks. Using negative binomial models, we estimate the relationship between aggregate speeds and crash likelihood on arterials. Notably, *differences* in percentile speeds were more informative than individual percentile speeds alone.

Arterials are complex roadways that serve multiple purposes. However, limiting the highest speeds and speed differentials may limit the number of crashes and injuries. This research suggests that probe vehicle speeds may provide a useful tool for investigating safety problems in the future. Further, speed differences, especially those at the higher end of the speed distribution, are a promising means of measuring the speed distribution as it relates to safety.

This research has three broad contributions for policy and practice:

- Develops a framework for assessing transportation safety programs and policies using public health principles
- Uses probe vehicle speed data to assess risk on roads at the corridor and network level
- Identifies high-end speed differences as performance metrics for proactively identifying roadway risk

Although this dissertation proposes a framework for transportation safety and demonstrates a promising application of probe vehicle speed data, future study is needed to better understand how public health ideas can influence transportation, and how probe vehicle speeds may be used in transportation practice.

CHAPTER 1 INTRODUCTION

BACKGROUND AND MOTIVATION

Road traffic crashes are one of the leading causes of death in the United States, with more than 35,000 deaths every year and over 100,000 injuries (CDC 2020). To prevent road traffic injuries and deaths, it is important to understand the causes for crashes, and implement countermeasures to address risk factors related to crashing.

Public health practitioners have developed methods to identify the causes of adverse health outcomes that is broad referred to as "the public health approach" (Centers for Disease Control and Prevention, n.d.) There are four basic steps to the approach:

1. Surveillance: *What is the problem?*
2. Risk Factor Identification: *What is the cause?*
3. Intervention evaluation: *What works?*
4. Implementation: *How do you do it?*

This approach is intended to be very broad and is applied to a wide variety of public health problems, from infectious diseases to chronic health problems, to injuries.

The problem of traffic crashes is clear. Thousands of Americans die on the roads each year and many more are injured (step 1). In this dissertation, we review research identifying the transfer of kinetic energy as the cause of traffic injuries (step 2), and propose a framework for prioritizing interventions to prevent and control the transfer of kinetic energy to the human body (steps 3 and 4).

Next, we describe a statistical analysis on a primary risk factor for traffic injuries: vehicle speed. Based on the estimated relationship between aggregated vehicle speeds and crashes, we propose performance metrics that may be used to be used for risk factor surveillance and intervention evaluation.

RESEARCH APPROACH

In this dissertation, we describe the history of injury prevention and control in public health and its role in transportation safety. Then we propose a framework for transportation safety policies based on the principles of injury prevention and control. Then, we expand on the public health practice of risk factor surveillance by assessing the relationship between aggregate vehicle speeds and crash frequency. We propose performance metrics to actively monitor vehicle speeds as a risk factor surveillance system for traffic safety.

CONTRIBUTIONS

This research makes several important contributions. First (1), we propose a framework for prioritizing traffic safety interventions and policies. This framework is based on the science of injury prevention and control. Most research on transportation and public health discusses health outcomes related to the transportation system. Instead, we propose that transportation professionals apply public health principles in their work to prevent adverse health outcomes. We will submit the chapter on this framework to a peer reviewed journal read by transportation professionals.

Second (2),we model the relationship between operational speeds and crash frequency using an increasingly important data source: probe vehicle speed data. Probe speed data is typically used to assess travel times on highway networks. This dissertation analyzes arterial roadways, which account for a large proportion of crashes, injuries, and deaths. The nature of the speed-safety relationship is likely very different on arterials and grade-separated highways.

Third (3), we propose different metrics based on probe vehicle speed data and apply it to the Georgia Department of Transportation (GDOT) arterial network. Current engineering practice relies on percentile speeds or other measures of central tendency to identify which roadways are likely to experience more crashes than others. This research suggests that *differences* in percentile speeds are more informative than percentile speeds alone. We propose using these metrics as a risk factor surveillance system in line with public health practice. Current engineering practice uses crash histories alone.

Thus, this research has implications for researchers and practitioners. Departments of Transportation face difficult decisions about how to prioritize limited budgets but are striving to prevent serious injuries and deaths on their roadway networks. The public health principles, framework, and performance metrics proposed in this research can assist transportation professionals in building safer roadways.

CHAPTER 2 TRANSPORTATION SAFETY AND PUBLIC HEALTH

Transportation planners, engineers, and public health professionals share a mutual interest in promoting safety and health. There are several notable examples of transportation and health professionals collaborating, from conducting Health Impact Assessments, incorporating health outcomes into the planning process, gathering data to evaluate transportation policies, and collaborating on transportation projects that promote healthy living or better access to medical care (Boarnet et al. 2012; FHWA 2012; Dannenberg et al. 2008; Meehan and Whitfield 2017; McDonald et al. 2014; Whitfield et al. 2017). These efforts reflect a sustained interest in improving health outcomes by minimizing transportation's negative influences and maximizing the positive ones.

In addition to individual efforts to promote health in transportation, there are many institutional level efforts by professional organizations to increase collaboration and provide guidance on how transportation and health professionals might collaborate. For example, the National Highway Traffic Safety Administration (NHTSA) was initially led by a medical doctor who developed a framework for thinking about injury prevention and control as a public health issue (Baker 1989, Runyan 1998). Consumer safety and occupational and public health advocates also played a key role in developing vehicle safety standards and creating legislation on intoxicated driving (Bonnie, Fulco, and Liverman 1999). These and other efforts led to traffic safety being named as one of the major public health achievements of the 20^{th} Century (CDC, 1999). Despite this progress, there is still a great deal of interest in the intersection of public health and transportation. More recently, the American Public Health Association, American Planning Association, and the Institute of Transportation

Engineers have all recently authored reports or sponsored initiatives highlighting transportation and health (APHA, n.d.; APA n.d.; ITE, n.d. Ricklin et al. 2012; Ricklin and Kushner 2013). Several journal articles and reports have been authored to assist professionals in each discipline by outlining the funding and planning processes specific to their profession, defining terms which differ between fields but have a similar meaning, and research roadmap for transportation and health (Malizia 2009; Dannenberg et al. 2021, Steedly et al. 2019). There are also growing efforts to train students in both transportation and health (Botchwey et al. 2009; Botchwey and Trowbridge 2011; Pollack et al. 2015).

Efforts to integrate processes and introduce siloed professionals are necessary and useful to promote collaboration. In addition to the many efforts to incorporate public health ideas and methods into vehicle design for occupant protection, many opportunities remain to help transportation professionals working on the built environment understand the methods and practices associated with public health.

Definition of public health and foundations of the field

Public health, like "engineering" describes a range of professionals with different roles and training. The Association of Schools and Programs of Public Health (ASPPH) defines 10 different professional categories: Behavioral and Social Science, Biostatistics and Informatics, Community Health, Epidemiology, Environmental Health, Global Health, Health Policy and Management, Health Promotion and Communication, Maternal and Child Health, and Minority Health and Health Disparities (ASPPH, n.d.). While the field includes a wide range of occupational categories and specialties, there are several underlying tenets of the profession that create shared concepts and goals of the field. In his seminal text, *The Untilled Fields of Public Health*, Charles E.A. Winslow defines public health as:

> *The science and the art of preventing disease, prolonging life, and promoting physical health and efficiency through organized community efforts for the sanitation of the environment, the control of community infections, the education of the individual in principles of personal hygiene, the organization of medical and nursing service for the early diagnosis and preventive treatment of disease, and the development of the social machinery which will ensure to every individual in the community a standard of living adequate for the maintenance of health.*
>
> (Winslow, 1920)

First, public health is focused on the *prevention* of disease to *promote* health and prolong life. Second, public health is focused on the health and wellbeing of populations, rather than individuals (Barry 1975). While individual efforts are necessary in public health, they are done in support of promoting population health, unlike medicine, which is primarily concerned with the health of individuals. Immediately following his definition of public health, Winslow notes that “many different experts of fundamentally distinct training, must contribute their special resources to the common task” (Winslow 1920). Thus, successful public health efforts are dependent on contributions from multiple disciplines. Winslow notes that there are seven types of qualified persons in public health: the physician, the nurse, the bacteriologist, the epidemiologist, the statistician, and the *engineer* (Winslow 1920, emphasis ours). The idea of engineers as public health professionals was present well into the mid-20th century when an editorial in the *American Journal of Public Health* made the point that "The engineer is, indeed, an increasingly strategic member of the health team" (AJPH, 1959).

Role of engineers in public health

Before Winslow identified engineers as one of the seven types of highly qualified persons engaged in public health, engineers had already made many significant contributions to the field and practice. Public health practitioners and epidemiologists typically consider John Snow's study of cholera in London to be the first example of modern epidemiology as he, with help from …, identified the vector of cholera to be contaminated drinking water, rather than an airborne miasma (Witcher 2020). This study led to engineer Joseph Bazalgette's plan to avert the water system to avoid contaminating drinking water with human and other waste. The collaboration between Snow and Bazalgette is just one of myriads of collaborations between epidemiologists and engineers that have solved public health problems (Witcher 2020).

The role of engineers in public health was both recognized and defined in the early half of the 20th century (Gelting et al. 2019; Witcher, 2020). In fact, one of the first sections created in the American Public Health Association (APHA) was the "Public Health Engineering" section, founded in 1911 (APHA, n.d.). The Public Health Engineering section was rebranded as the "Engineering and Sanitation" Section in 1955 and the "Environment" Section in 1970, reflecting the gradual decline in engineers being considered public health professionals in lieu of simply affecting public health through their decisions (APHA, n.d.).

Although there is an increasing effort to engage engineering and public health students in joint coursework, "public health engineering" was recognized as its own separate discipline from other civil, sanitary, or even environmental engineers (Phelps, 1931). In a paper delivered to the APHA’s public health engineering section, Phelps defines public health engineering as “an essential calling, the prime object of which is to control the factors of the physical environment as they especially affect the health and welfare of aggregates of people” (Phelps 1931). This is consistent with public health’s focus on population health, and unlike medicine’s focus on individual health. Similarly, transportation systems engineers build transportation networks for populations, and must prioritize safety at the aggregate level.

APHA’s Public Health Engineering section regularly debated what constitutes public health engineering, and developed sample curricula (Hyde 1936; Clark 1947). Engineers were not only engaged in debating their role in public health, but also assumed leadership roles in the field. The first director of the Communicable Disease Center, now referred to as the Centers for Disease Control and Prevention (CDC), was a civil engineer and engineers far outnumbered physicians at the new agency (Earnest et al. 2006; Witcher 2020). However, public health and engineering grew increasingly specialized and gradually apart as environmental health became its own separate field different from engineering (Gelting et al. 2019). The Epidemic Intelligence Service, one of CDC’s primary means of training public health professionals, graduated only 7 engineers between 1951 and 2000, despite over 2,400 other health professionals trained in that time (Thacker, Dannenberg, and Hamilton 2001).

Despite the relative lack of professional recognition of engineers in public health, there are renewed efforts to train engineers in public health, and vice versa. Today, the Johns Hopkins University Bloomberg School of Public Health and the University of North Carolina at Chapel Hill Gillings School of Public Health incorporate engineering into their curricula

(Gelting et al. 2019). In fact, the Department of Environmental Health and Engineering is jointly hosted by the School of Public Health and the School of Engineering (https://ehe.jhu.edu/about/). Several engineering schools also incorporate public health topics into their engineering curricula, including Tufts University, Columbia University, Stanford University, and Georgia Institute of Technology (Gelting et al. 2019). Most engineering efforts in public health are focused in environmental and occupational health (Earnest et al. 2006, Gelting et al. 2019).

The built environment can both facilitate and be an impediment to health. Civil and environmental engineers thus have an outsize role in public health by building, designing, and maintaining the built environment, whether water or transportation systems. Transportation planners and engineers play an important role in protecting and promoting public health by setting priorities for where and what types of infrastructure is built, and designing the infrastructure itself. In the early half of the 20^{th} century, engineers played a critical role in altering the built environment so that human populations could avoid exposure to disease vectors and their associated infectious agents (Gelting et al. 2019). Engineers and planners understood their role to alter the built environment to prevent or control the transmission of a pathologic agent to human populations. Similarly, transportation planners and engineers have a duty to protect the population and promote health by creating a built environment that decreases exposure to dangerous levels of kinetic energy that cause injury and death. Direct collaboration between public health practitioners and planners is important in these programs. Writing on the duties on the “Public Health Engineer,” Clark emphasizes that engineers working in public health are not simply those at health departments, noting their roles in industry, other government agencies, and academia (1937). Instead, Clark emphasizes the adoption of public health principles in engineering practice, writing:

> *In the field of public health, the most effective development of an opportunity rests mainly on one personal attribute, a common ingredient in all successful public health workers, whether engineers, epidemiologists, nurses, or others, and that is a public health consciousness (1937).*

Clark's diagnosis is correct that one does not need to be an engineer or planner working at or with a health department to practice public health. Rather, one needs to adopt the underlying principles of public health in their work. The existing "E's" framework does not adopt a public health consciousness. Revising the underlying frameworks for transportation safety professionals can help transportation professionals adopt a public health consciousness. Efforts to increase cross-training in public health, engineering, and planning are important to establish this "consciousness." However, the frameworks that underlie transportation safety programs should also reflect public health thinking. As a public health problem, traffic injuries need to be understood in the context of population health and prevention. Using a framework based on the public health approach will help practitioners from other disciplines implement public health thinking into their work and decision making.

Injuries as an epidemiologic problem

With increasing industrialization and the rise of the automobile, the burden of injuries was of increasing interest to the general public. The epidemiology of injuries was clear: people were dying from injuries, and more died year after year. In 1921, 12,500 people died in traffic crashes, and by 1926, more than 25,000 died on America's roads (Graham 1924; Barber

1927). At the time, data on crashes was not standardized, and many states did not mandate data collection at all, but the causes of the increase in crashes was likely related to improved data collection as well as increases in the amount of vehicles, and their horsepower (Graham 1924). The issue had become so prominent that Secretary of Commerce Herbert called for the first National Conference on Highway Safety to better understand the causes and potential solutions for traffic crashes, presided by the Secretary himself, and featuring an opening session by President Calvin Coolidge (Damon 1958). Although human beings have attempted to prevent and avoid injuries for millennia, it was not until this time that we began to understand the *etiology* of injuries. Knowing the causes of disease or injury is critical for implementing effective countermeasures. For example, one must know whether an infectious disease is caused by a virus, bacteria, or fungi to effectively treat and prevent it. As the burden of injuries increased in the early half of the 20th century, researchers began to conceive of injuries, and traffic injuries specifically as a public health problem with causes that could be defined. Rather than accept crashes as "accidents" or "acts of God" as was the status quo at the time, researchers identified risk factors such as driver intoxication and vehicle speed as key risk factors in crashes, injuries, and deaths.

Human behavior as the primary cause of crashes

Advocacy groups and trade organizations began pushing to collect data and determine the causes of crashes, including the National Safety Council, the American Automobile Association, the U.S. Chamber of Commerce, and the Automobile Chamber of Commerce (Damon 1958). Notably, the Chief Engineer and Director of the Safety Division at the National Safety Council (NSC) began studying the causes of traffic deaths and advocating for a coordinated system to collect data on road traffic crashes nationally (Williams 1925;

Williams 1927; Williams 1935-36; Williams 1937). The NSC, led by Williams, repeatedly pushed the idea that the primary cause of crashes was human behavior, writing “We know that the human factor, the drivers and pedestrians, is more important in causing or averting an accident than either the car or the highway” (Williams 1935-1936). Based on the understanding the human behavior was the primary cause of crashes, Williams and the NSC thus promoted the “3 E’s” paradigm which focused on balancing education, enforcement, and engineering efforts to prevent crashes (Williams 1937).

The “E’s” Framework of Traffic Safety

The E’s framework was first proposed by Julien H. Harvey, a Kansas City transportation planner, in 1923 (Groeger 2011). They were refined and heavily promoted by the National Safety Council, and specifically by its Chief Engineer, Sidney Williams (Damon 1958). Williams conception of the traffic safety emphasized good public health practice in that he promoted prevention. However, Williams claimed that a “balanced approach” between the three Es would reduce deaths by 50% (Williams 1935-1936). Further, he tended to emphasize behavioral change above all other interventions, writing “we know that the human factor, the drivers and pedestrians, is more important in causing or averting an accident than either the car or the highway” (Williams 1935-1936). Williams was also a strong proponent of school-based programs to encourage children to not get hit by cars as a primary means of injury prevention (Williams 1937). The E’s framework and the emphasis on human behavior still prevails today. The National Highway Traffic Safety Administration (NHTSA), the federal agency dedicated to transportation safety claims notes the 94% of crashes are the result of human error and includes the E’s as its primary framework for thinking about transportation safety (Mendoza et al. 2017; Tang et al. 2018). Focusing on road user behavior and education is indicative of the current approach lacking a public health consciousness. According to the social ecologic model, people operate in a system that presents choices for behavior (Hanson, Vardon, and Lloyd 2004; Mercy, Mack, and Steenkamp 2008). Similarly, education is not universal and the choices available are not uniform (Nilsen, Bourne, and Verplanken 2008). A public health approach seeks to correct for these discrepancies and to eliminate risk in the population. Strategies that implicitly or explicitly benefit one population or another are contrary to the goals and objectives of public health.

The etiology of injuries

While one area of research was primarily concerned with the cause of crashes, others became interested in the cause of injury. Public health researchers began investigating the causes of injuries in the 1920s and 1930s as traffic and occupational injuries began to increase. This led to the founding of a new field to better understand and control injuries.

Energy transfer as the primary cause of injuries

Modern injury prevention control traces its roots to DeHaven's 1942 analysis of falls from a range of heights (Guarnieri 1992; Bonnie, Fulco, and Liverman 1999; Robertson 2018). DeHaven, a mechanical engineer and former pilot, believed that airplane and motor vehicle crashes were not the result of random occurrences, but could be scientifically studied (DeHaven 1942). DeHaven studied 8 cases of people that had fallen intentionally or unintentionally from a range of heights that he identified in news articles, then obtained information about their medical outcomes, height, and weight, and used the information to calculate the force at which they hit the ground (DeHaven 1942; Gangloff 2013). From these studies, DeHaven concluded that the human body could tolerate substantial force if it were dissipated over a larger surface or could be absorbed (Gangloff 2013). At the time, most medical doctors felt that surviving a fall or traffic crash was random, and that one could not prevent injuries in a traumatic event (Gangloff 2013). DeHaven's analysis of falls identified *kinetic energy* as the cause of injury and proposed that distributing or absorbing this energy could prevent injuries and save lives (DeHaven 1942). Further, DeHaven's analysis highlighted how peak forces at the point of contact determine the extent of injury. Thus if a crash does occur, the forces could be dissipated by slowing the acceleration of one or both objects, or by dissipating the point of contact over space. Both measures decrease the amount of energy transferred to the human body in a crash, and could be used to prevent serious injuries. This relationship was then used to develop countermeasures such as seatbelts, airbags, and crumple zones to mitigate the transfer of kinetic energy to the human body.

DeHaven later founded the Automotive Crash Injury Research Project at Cornell University, and developed methods to determine the crashworthiness of automobiles (Gangloff 2013). DeHaven understood that his ideas about injury prevention had clear implications for public health and injury prevention, and believed that collaboration between engineers and medical doctors would help promote his ideas. After reaching out to the Secretary of the American Medical Association AMA, he was told that no such collaboration between engineers and physicians existed and that he would be best to contact rodeo clowns as they knew how to safely take a fall (Gangloff 2013).

Although DeHaven was rebuffed by the American Medical Association, public health professionals also took a keen interest in injury prevention around the same time as he was investigating why some people were injured in similar falls while others were not. James Gibson presented to the American Public Health Association in November 1948 on injuries as an epidemiologic problem (Gordon 1949). In his presentation, Gordon proposed considering injuries within the classic epidemiologic triad, writing:

> *The causative factors in accidents have been seen to reside in the agent, in the host, and in the environment. The mechanism of accident production is the process by which the three components interact to produce a result, the accident: it is not the cause of the accident.* (Gordon, 1949).

The epidemiologic triad is one of the most basic of public health models, stating that disease results from the interaction between a host, an agent, and the environment. All three must be present to cause disease or injury, offering opportunities to prevent disease or injury by intervening to eliminate one of the poles or the interaction between two. Gibson also noted that injuries demonstrated similar characteristics to infectious disease: point outbreaks, seasonal variation, and characteristic distributions (Gordon 1949).

Further, Gordon framed the interaction within the larger social context, well in line with later iterations of the epidemiologic triad such as social-ecologic model. He notes that beyond the simple interaction between host-agent-environment, "whatever the kind or nature of mass disease or injury, the part exerted by the socioeconomic environment is probably the most neglected of any epidemiologic influence" (Gordon 1949). This focus on the context of where and how injuries occur was a departure from other efforts which prioritized education and enforcement of individual users. This research thus laid the groundwork for later efforts to approach injury prevention, and traffic crashes specifically using a public health approach.

Energy as the agent of injury

William Haddon was a medical epidemiologist interested in injury prevention and the work of DeHaven and Gordon. Haddon's work in the 1950s and 1960s built on prior research by codifying the host-agent-environment relationship more specifically, noting that the agent in injuries is energy, not the physical object that delivers it (Haddon 1980). Gordon proposed the initial host-agent-environment relationship by stating that the human being is the host, the agent was the object causing injury (e.g., a loose floorboard or the windshield of an automobile), and the environment encompassed the physical location as well as the socioeconomic environment of the injured person (e.g. a crash occurring in West Virginia is different than a crash occurring in Southern California). Haddon modified this understanding by using DeHaven's theory that the agent is energy, and expanded DeHaven's theory to include chemical, thermal, or radiation energy in addition to mechanical (Haddon 1980). The transfer of energy is necessary to cause injury in the same way that biologic agents are necessary for certain diseases. The distinction is important and is best demonstrated by an example. To develop malaria, a human host must be exposed to one of several species from the *Plasmodium* genus. Typically, a human host is exposed to a plasmodium via a mosquito bite. The mosquito, in this case, is a vector and the agent of disease is the plasmodium. Similarly, to be injured, one need be exposed to energy. The vehicle or mode of transportation is akin to a vector. The distinction is important if one intends to prevent disease or injury. In the malaria example, eliminating the vector is effective at first, but when efforts to destroy mosquitoes fail, interventions against the plasmodium are needed. Similarly, focusing only on eliminating sharp edges in vehicles misses the opportunity to absorb and dissipate kinetic energy in other ways.

Bridging Public Health Theory and Practice

In addition to refining the host-agent-environment framework, Haddon developed a tool for practitioners to identify different preventive measures based on the triad. The tool is organized as a matrix with host, agent, and environment as columns, and the temporal phases of an event as the rows, split between pre-event, event, and post event (Haddon 1999; Haddon 1980). The tool is intended to help practitioners think through the potential interventions, and when they might be implemented. Haddon's Matrix can be applied to a road traffic crash (the event) by filling interventions into each cell corresponding to the specific portion of the epidemiologic triad, and whether it is a primary (pre-event), secondary (event), or tertiary (post-event) preventive effort.

Haddon's conception of injuries in the epidemiologic triad are a "Component" model, which identifies all the individual contributing parts or units (Hughes et al. 2015). By adding the temporal component, Haddon's Matrix is both a "Component" and a "Sequence" model that describes the series of events resulting in event in addition to noting the components of it (Hughes et al. 2015). Component and sequence models of road safety are used to help practitioners develop and assess countermeasures and determine causes (Hughes et al. 2015). Although not explicitly cited within the matrix, Haddon wrote extensively on what he referred to as "active" and "passive" measures (Haddon 1975, Haddon 1980). Passive measures are those that require little to no individual action, while active measures require increasing individual effort (Haddon 1974; Haddon 1975; Haddon 1980). An example of active and passive measures in oral public health is brushing one's teeth versus fluoridating water supplies. Both are effective in preventing cavities, but fluoridation requires little to no effort from individuals and intervenes at the population level. Both are necessary, but the health benefits of fluoridation require government action. Despite Haddon's personal preference for passive measures, they are notably absent in his matrix. Further, the matrix does not distinguish between population level and individual interventions. Haddon adamantly argued against behavioral approaches that emphasizes "victim-blaming" (Haddon 1980). Thus, the Haddon Matrix cannot be considered an "Intervention" model used to analyze or prioritize road safety policies (Hughes et al. 2015). Runyan attempted to update the Haddon Matrix by adding a 3rd dimension to it to prioritize policies (Runyan 1998). The "3 Dimensional Haddon Matrix" is comprehensive, but the 36 different criteria can prove unwieldy to even the most dedicated practitioners. Although a simpler model is less specific, it is likely easier to understand and be used by practitioners.

Haddon recognized the shortcomings of his matrix for thinking about injury prevention policies systematically and suggested a rank order list of interventions for injury prevention purposes, which are referred to as "Haddon's Strategies" in injury prevention and control listed in the "Strategy" column of Table 1 below (Haddon 1970, Haddon 1980). These strategies can be described as Haddon's attempt at an Intervention model for prioritizing policies (Hughes et al. 2015). In the "Application to traffic safety" column we list examples of Haddon's strategies in traffic safety (Table 1). In developing the strategies, Haddon notes that any may be used in prevention and control, but when there is more potential energy involved, countermeasures noted earlier in the sequence should be used (Haddon 1980). Although Haddon's contribution is clear about how to prioritize interventions based on kinetic energy and applies sound public health science for individual instances of injury, it does not necessitate that interventions should be considered for their population level health impacts.

Table 1. Example applications of traffic safety associated with Haddon's ten countermeasure strategies for injury prevention

	Strategy	**Application to traffic safety**
1.	*Prevent the marshalling of the form of energy in the first place*	Institute land use policies that encourage people to walk or cycle rather than drive
2.	*Reduce the amount of energy marshalled*	Reducing vehicle speed
3.	*Prevent the release of energy*	Create a roll cage in a vehicle, emergency braking systems
4.	*Modify the rate of spatial distribution of the release*	Wearing a seatbelt, jersey barriers, crumple zones, altering curb radii
5.	*Separate in space or time, the energy from being released from the susceptible structure*	Leading pedestrian interval, protected left and right turns
6.	*Does not separate in time or space but by the interposition of a material "barrier"*	Wearing a motorcycle or bicycle helmet
7.	*Modify the contact surface, subsurface, or basic structure*	Redesigning an automobile interior or exterior
8.	*Strengthen the structure, living or unliving, that might otherwise be damaged by the energy transfer*	Build reinforced passenger cabin to prevent crushing energies, encourage people to exercise
9.	*Move rapidly in the detection and evaluation of the damage that has occurred or is occurring and to counter its continuation and extension.*	Emergency notification systems, emergency medical services
10.	*All measures between the emergency period following the damaging energy exchange and final stabilization of the process*	Trauma care, Rehabilitation programs after being involved in a crash

Haddon's Legacy of public health in road safety

Haddon remains one of the most important figures in injury prevention and control and developed the underlying theories and concepts that students of injury prevention learn at schools of public health (Baker 1989; Runyan 2003; Bonnie and Guyer 2002). In addition to his academic accomplishments, Haddon made substantial contributions to safety practice and policy by making substantial contributions to the Federal Motor Vehicle Safety Standards, as the first Administrator of what would later become NHTSA, and longtime president of the Insurance Institute for Highway Safety (IIHS) (Sielski 1967; Kahane 2015). His influence on these organizations is clear. NHTSA's role as vehicle safety regulator has saved thousands of lives by implementing countermeasures that dissipate and absorb energy such as seat belts, airbags, and roll cages (Kahane 2015). Further, the approach to vehicle safety policy and regulation has tended to favor passive rather than active measures as safety tasks such as automated emergency braking are incorporated into vehicle fleets (Kahane 2015). NHTSA has regulated these features into vehicles, and IIHS has consistently tested and promoted them as a nonprofit organization. Vehicle design and safety standards have prevented many injuries and deaths for vehicle occupants. Occupant protections are an excellent example of the sound public health thinking expounded by Haddon and others. Despite the remarkable progress for vehicle occupants, road traffic deaths and injuries remain high, and deaths among vulnerable road users have increased in recent years (National Center for Statistics and Analysis 2020). The public health approach to injury prevention and control has been systematically applied to vehicle occupant protection, primarily through vehicle design regulations, and consumer advocacy tests such as those performed by the Insurance Institute for Highway Safety (IIHS). There is a strong emphasis on safety in transportation infrastructure design, but the framework for understanding safety was not developed using the same public health principles as those developed by Haddon and others for vehicle design. While improvements in geometric design and pavement technologies have improved transportation safety, the United States still experiences far more traffic deaths than other high income countries when adjusting for both population and vehicle miles traveled (Sauber-Schatz et al. 2016).

Safe Systems and Vision Zero

Vision Zero is an increasingly popular transportation safety policy in American cities (Kim et al. 2017). Vision Zero typically calls for a "Safe Systems" approach to road safety where safety is the top priority, and that all deaths can be prevented in the long term (Kim, Muennig, and Rosen 2017). Vision Zero programs frequently call for collaboration between transportation and public health agencies and practitioners (Fleisher, Wier, and Hunter 2016). The role for public health practitioners in these programs is typically related to data collection and evaluation, which are core public health activities (Fleisher, Wier, and Hunter 2016). However, Vision Zero programs can help public health and transportation professionals collaborate, but should be based on the underlying philosophy of prevention, risk factor mitigation, and promotion of protective factors inherent in public health (McAndrews 2013; Kim, Muennig, and Rosen 2017). Sweden, the Netherlands, and the United Kingdom began implementing Safe Systems approaches in the late 1990s and early 2000s, and traffic deaths have declined in these countries nearly 5% each year per capita (Hughes, Anund, and Falkner 2015). Notably, these international Vision Zero/Safe Systems/Systematic Safety efforts emphasize the traffic safety as a public health problem, emphasizing the release of kinetic energy as the agent responsible for injuries, and developing interventions based on the biomechanical limits of the human body (Corben et al. 2010; Belin, Tillgren, and Vedun 2012; Kristianssen et al. 2018). In fact, many plans specifically cite the work DeHaven, Gordon, and Haddon when describing the origins of their safe systems programs (DeHaven 1942; Gordon 1949; Haddon 1970; Haddon 1980; Robertson 1983; Belin, Tillgren, and Vedun 2012; Kumfer et al. 2019a).

Vision Zero and Safe Systems approaches take Haddon's work on the theoretical basis for transportation safety and translate it into policy. Claes Tingvall, the Director of Traffic Safety at the Swedish Roads Administration and architect of Sweden's Vision Zero policy, is a trained injury epidemiologist, and regularly cited Haddon's work when explaining the basis of Vision Zero (Belin, Tillgren and Vedung 2012). In fact, when first describing what he then referred to as "The Zero Vision" at the "Transportation, Traffic Safety, and Health Conference" in 1997, Tingvall described a three-step approach for his "Zero Vision" that featured both active and passive safety measures to control or eliminate kinetic energy in traffic crashes (Tingvall 1997). Summarizing his approach, Tingvall notes that key to preventing injuries and deaths on roads is controlling or preventing the transfer of kinetic energy (Tingvall 1997). During the same conference, NHTSA Administrator Ricardo Martinez presented on NHTSA's approach to injuries, and emphasized the 4 E's of engineering, enforcement, education, and economics, and noted the importance of partnerships rather than prioritizing any interventions (Martinez 1997).

The E's framework continues to exist today in the United States. The FHWA Strategic Plan includes a "Towards Zero Deaths" goal that emphasizes the 4Es: education, enforcement, engineering, and emergency medical and trauma services (Mendoza et al. 2017). This approach is reflected in many municipal Vision Zero plans (Fleisher, Wier, and Hunter 2016). The emphasis on "Es" is useful for suggesting collaboration but misses the point that Vision Zero is rooted in a scientific, public health approach (McAndrews 2013).

The inadequacy of the E's framework is evidenced by the frequent addition of new E's beyond the traditional engineering, enforcement, and education to include equity, evaluation, emergency services, economics, ergonomics, exposure, enablement, and examination of competence and fitness (Groeger 2011; McIlroy et al. 2019). If the initial E's sufficiently described the safety problem, further E's would not be needed. Simply adding alliterative titles to the initial list does not help prioritize interventions or suggest anything about their effectiveness at the individual or population level. Adding more E's does little more than dilute responsibility and focus. Further, the E's framework, even with only the initial 3 E's implies a false equivalency between the different factors and interventions. Engineering, enforcement, and education are not equally effective. The E's paradigm neglects the public health principles which stipulate that population level interventions that require less individual effort should be prioritized, and that one need focus on the pathologic agent (in this case, the transfer of energy). If Vision Zero and Safe Systems philosophies require a paradigm shift, it is necessary to suggest that a new framework be used in transportation safety.

APPLYING THE HEALTH IMPACT PYRAMID TO TRANSPORTATION SAFETY

Instead of simply collaborating with public health practitioners, transportation professionals, including engineers, must understand how to apply public health concepts in traffic safety. The principles of prevention, a focus on population health, and an understanding of the specific causes of injury can help engineers and planners implement effective safety policies.

Thus, we propose that the structure of the Health Impact Pyramid be used along with the principles outlined by Haddon and others as the framework for Vision Zero policies (Frieden 2010). The E's framework presents a false equivalence in terms interventions, and Haddon's concepts do not incorporate population health impacts despite firm grounding in science and prevention. The Health Impact Pyramid is a general framework for public health action that prioritizes interventions that have increasing population health impact and decreasing individual effort needed (Frieden 2010). The five-tier pyramid is shown in Figure 1 below. The "Hierarchy of Controls" is a similar framework used in occupational health and safety, displayed in Figure 2 (Halperin 1996; National Institute of Occupational Safety and Health 2016). Unlike Frieden's Health Impact Pyramid, the Hierarchy of Controls is organized by effectiveness, with the most effective strategies at the top, and least effective strategies at the bottom. The Hierarchy of Controls features many of Haddon's Strategies (e.g. one could argue that "preventing the marshalling of energy is akin to "Elimination"), but simplifies them into 5 categories.

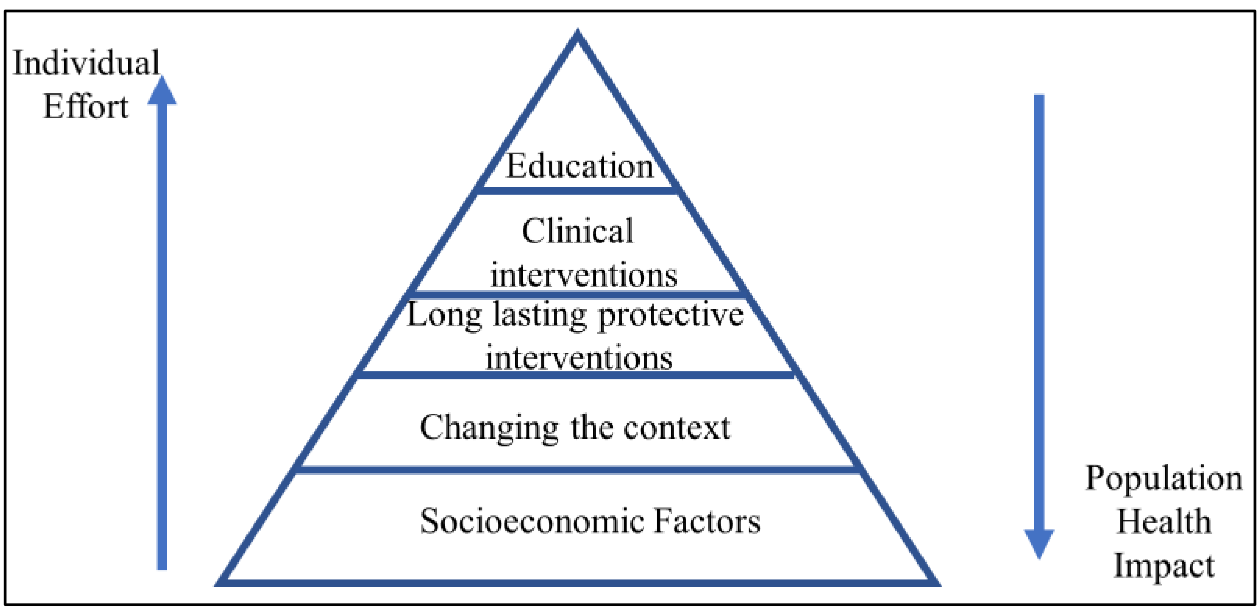

Figure 1. Health Impact Pyramid (adapted from Frieden 2010)

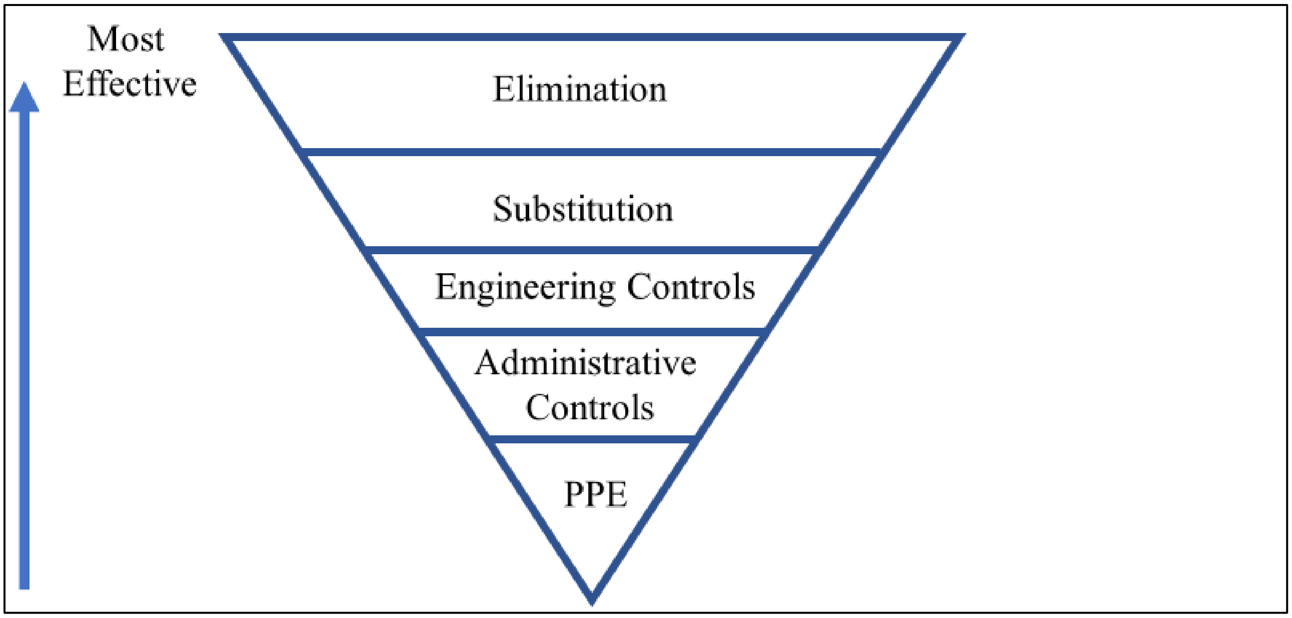

Figure 2. Hierarchy of Controls (Adapted from the National Institute for Occupational Safety and Health 2015)

Elements of Frieden's Health Impact Pyramid and the Hierarchy of Controls are useful for analyzing road safety policies and interventions, but each has shortcomings when applied to road safety policy. Frieden's Health Impact Pyramid is intended to analyze population health impact in addition to the effectiveness of any intervention while the Hierarchy of Controls does not explicitly include references to population health impact. In addition, the Health Impact Pyramid includes Socioeconomic factors at its base. This is absent in the Hierarchy of Controls. Conversely, the Health Impact Pyramid also includes factors that are not relevant to road safety such as "Clinical Interventions," which are for the most part not useful in preventing or controlling traffic related injuries.

The Health Impact Pyramid is intended to help prioritize specific interventions (e.g. fluoridating water to "change the context"), but is also intended to be applied to policy (e.g. changing federal water quality standards to require fluoridation). Frieden notes that:

> *Interventions at the top tiers are designed to help individuals rather than entire populations, but they could theoretically have a large population impact if universally and effectively applied. In practice, however, even the best programs at the pyramid's higher levels achieve limited public health impact, largely because of their dependence on long-term individual behavior change* (Frieden 2010).

Policy is critical for exposing a larger population to effective interventions. However, the success of interventions that require increased individual effort is contingent on individual decisions. Even when legally required, educational and behavior focused interventions are less effective than those that change the context in which people operate. Therefore, a public health framework applied to road safety should be used to evaluate individual interventions as well as policies that regulate them.

The Hierarchy of Controls has been applied to road safety to codify different interventions and link them to sustainability policy (McLeod and Curtis 2020). The Hierarchy of Controls includes explicit inclusion of “Engineering Controls” is critical for road safety. Vehicle and roadway engineering are important facets of a traffic injury prevention and control strategy. However, we argue that vehicle engineering and roadway engineering differ in their application to population health and whether they require individual effort. For example, automated emergency braking is an important strategy for preventing crashes but is only useful if vehicles have the technology installed. On the other hand, built environment interventions apply to all road users in an area where implemented and can thus increase safety for a larger population. Either the Health Impact Pyramid or the Hierarchy of Controls could be applied to transportation safety. However, elements of each are relevant to road safety. Therefore, we propose a new framework for road safety. This framework is not intended to be applied to other modes of transportation such as marine and air transport, which present other issues that may be similar, but are different from those on roads.

By combining elements of the Health Impact Pyramid and the Hierarchy on Controls, we propose “The Safe Systems Pyramid.” The pyramid is presented in Figure 3 and described in the sections that follow. Table 1 below notes each level of the pyramid and lists examples of interventions related to each tier. In descending order, the pyramid consists of education, active measures, latent safety measures, the built environment, and socioeconomic factors (Table 1). Uptake, effectiveness, and the size of affected population all influence the population health impact of any intervention or policy. In general, going down the pyramid from education to socioeconomic factors increases the likely uptake as traversing down the pyramid requires less individual effort. The size of the affected population as interventions move down the pyramid are less individually focused. For example, while education can theoretically reach a large population, it is not universally accessible, and requires individuals to process and interpret it in the same manner. Similarly, broadly applied built environment measures affect any person traveling in that environment, while vehicle-based active and latent safety measures are contingent on their prevalence in the vehicle fleet, and people owning a vehicle with different safety features. Many of these features are not standard. Notably, population-level interventions are likely to shift maintenance and liability costs away from individual road users to those that design and operate the system itself. These costs should be considered in the context of whether the interventions reduce injuries, as reductions in injuries and deaths may outweigh any additional increase in cost or liability. Last, the pyramid does not account for the effectiveness of any individual intervention as it is expected that engineers and planners would only prioritize interventions they consider to be effective at reducing traffic injuries and deaths.

Policymakers and practitioners should apply evidence-based interventions. However, traveling down the pyramid is likely to increase the size of the population exposed to protective factors, as well as increase uptake. Thus, even if measures at the bottom of the pyramid have a smaller estimated effect size, the effect on overall population health is larger. Similar to interventions at the base of the Health Impact Pyramid, interventions at the base of the pyramid that change the built environment and socioeconomic factors often require substantial political will (Frieden 2010). While the upfront cost may exceed that of interventions at the top of the pyramid, the unit cost per injuries prevention is likely much less when intervening at the population level.

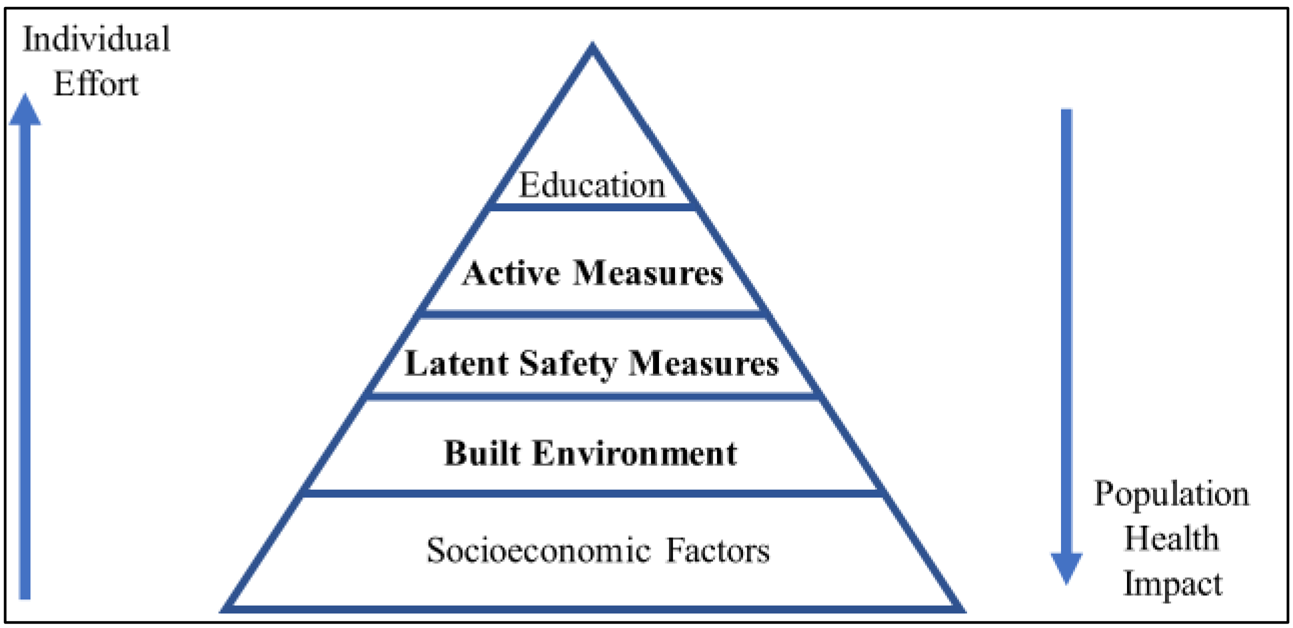

Figure 3. The Safe Systems Pyramid

Table 2. Summary table of tiers with intervention examples

Tier	Approach to prevention	Programs and interventions	Relevant policy
5	Education	Driver education programs, Slow Down Campaigns	Driver's education requirements for licensing
4	Active Safety Measures	Signals and signs indicating that one should stop or yield, forward, rear, and side collision warning, seat belts, helmets	Standards and guidance on where to place signs and signals, vehicle standards requiring safety features
3	Latent Safety Measures	Signal timing that encourages slower traffic progression, Leading pedestrian intervals, Air bags, automated emergency braking systems, speed governors, alcohol ignition interlocks	Standards and guidance on signal placement and cycle length, vehicle standards requiring the installation of latent safety features
2	Built Environment	Roundabouts, speed humps, chicanes, raised crosswalks	Federal, state, and local design guidance
1	Socioeconomic factors	Reduced poverty, affordable housing, zoning reform; education status	Zoning policies, housing policy, health insurance policies, labor policy

Socioeconomic factors

In Figure 1, at the base of the pyramid in the first tier are the interventions aimed at socioeconomic determinants of health, followed by those that change the context for health: protective interventions with long term benefits, clinical interventions, and counseling and education at the top (Frieden 2010). In the proposed safety pyramid, we maintain the socioeconomic determinants of health at the base. In their review of 121 road safety models, Hughes et al. point out that the social and economic factors are largely left out of models of road safety policy (2015). This contrasts with other public health issues. One of the most widely cited models in public health, Bronfenbrenner's social-ecologic model places the epidemiologic triad within the larger social and economic context that influences decisions and health behaviors (e.g. one's decision to speed or wear a seatbelt is also conditional on the social, cultural, and economic environment) (Runyan 2003). Although both Haddon and Gibson recognized the importance of these factors, they are frequently left out of models of road safety policy (Hughes et al. 2014). Thus, when place in the health impact pyramid, socioeconomic factors lie at the base.

Social and economic factors influence one's need to travel in the first place, potentially increasing exposure over time, but also dictate when and where one needs to travel. For example, a lower income person who works the night shift may need to travel to work late on a Saturday night when sight distances are poor and there are more intoxicated drivers on the road. In additional to the temporal variation in risk, risk of injury is not evenly distributed in space as low-income people, Black, Hispanic, and Indigenous people are be more likely to live near dangerous intersections, higher volume roadways or on a street that lacks sidewalks (Cubbin, LeClere and Smith 2000; Cubbin and Smith 2002; Schulz et al. 2002; Ameratunga et al. 2006; Morency et al. 2012; Rossen and Pollack 2012). All these factors present serious risk to a large number of people, but are not accounted for in traditional models of traffic safety. Thus, interventions addressing social determinants of health can help reduce road traffic injuries. The fundamental societal changes required to address these issues are typically outside a traffic safety policy, but should be viewed as supportive and connected to transportation safety as these factors also influence travel behaviors and culture.

Built environment

The next level of the health impact pyramid (Tier 2 in Figure 3 and Table 2) is “Changing the context,” which we replace with “Changing the built environment.” The Built Environment tier consists of mostly engineering improvements that might be prioritized in the Hierarchy of Controls, but also influences the nature of one’s exposure, similar to “Substitution” in the Hierarchy of Controls. For example, if a safer walking environment encourages a walking trip rather than a driving trip, it decreases overall exposure to others on the road.

Civil engineers play an outsize role in shaping the built environment, which plays an outsize role in health, especially in transportation safety. Many of the safety interventions in the upper levels of the pyramid are related to vehicle design, which is typically outside the purview of civil engineers. However, this framework highlights the importance of prioritizing built environment interventions for population level improvements over vehicle technologies, which may take many years to develop and have limited uptake.

Changes to the built environment can have large up-front costs and be politically challenging to implement but tend to be cost effective when implemented correctly in the long term (Peek-Asa and Zwerling 2003, Prüss-Üstün and Corvalán 2007). A Cochrane systematic review of controlled before and after studies of area-wide traffic calming effects found an approximate 11% reduction in fatal and non-fatal injuries associated with these interventions (Bunn et al. 2003). Modifications to the built environment can also have a direct influence on the transfer of energy by changing the speed or angle at which vehicles might collide by using treatments such as guard rails, medians to separate opposing directions of traffic, elevated stop lines, raised crossings, raised intersections, roundabouts, “centerline hardening”

(Candappa et al. 2015; Kumfer et al. 2019a; Kumfer et al. 2019b; Hu and Cicchino 2020). Should high speeds be necessary for vehicles, built environment treatments can also separate users in space using controlled access for very high speeds, and sidewalks or cyclepaths in environments where pedestrians and cyclists will travel (Furth, Mekuria, and Nixon 2012). Beyond engineering treatments, the built environment also includes the land use, population density, and access to destinations which can influence the distance travelled and mode (Sallis et al. 2016; Stevenson et al. 2016; Boulange et al. 2017). Compact built environments that require less driving or provide the option to not drive are excellent examples of reducing the amount of force marshalled (via walking or cycling instead of driving), or reducing the time exposed to a higher speed crash (via driving a shorter distance).

Importantly, changes to the built environment affect the entire speed distribution, rather than only those breaking the law or speeding excessively. In-person speeding enforcement is likely to target the fastest drivers, which is akin to only targeting the “sick” individuals rather than the entire population (Richter et al. 2006). Instead, good public health practice shows that the largest population health benefit is in shifting the entire risk curve of the population (Rose 2001; Farley and Cohen 2006). The population health benefit of shifting all speeds will likely exceed the health benefit of only targeting the highest speeds (Richter et al. 2006). Although they pose larger up-front costs, may take more time to implement, and require more political will, built environment interventions can help reduce risk for traffic injuries systematically. They can do so by altering the angle and speed at which collisions occur, separating modes when the amount of energy transferred is high, allowing people to reduce their overall exposure time, and providing options that marshal less energy in the first place.

Thus, built environment interventions merit substantial investment for interventions in Vision Zero and other traffic safety programs.

Latent safety measures

Next, “long lasting protective interventions” (Tier 3 in Figure 3 and Table 2) is replaced by “latent safety measures.” In Frieden’s initial conception of the pyramid, long lasting protective interventions include measures such as immunizations and colonoscopies, which are highly effective, but are applied individually, rather than to the population (Frieden 2010). Similarly, latent measures in transportation such as airbags and automated emergency braking are highly effective and act by decreasing the latent level of risk without requiring human intervention (Baker and Haddon 1973; Dumbaugh, Saha, and Merlin 2020). These would be considered “Engineering Controls” in the Hierarchy of Controls. However, to achieve the maximum population health impact, these measures require a high percentage of individual uptake. Many latent measures are focused on vehicles themselves as one of the primary vectors for transportation injuries. latent safety measures include crashworthiness and crash prevention technologies built into vehicles via design and automation. Examples of latent measures include improved vehicle interiors designs to mitigate the transfer of energy to vehicle occupants, exteriors that mitigate the transfer of energy to other vehicles and vulnerable road users, automated emergency braking, lane departure prevention, and daytime running or automatic headlights that improve sight distances (O’Neill 2009; Hu and Klinich 2015; Cicchino 2017; Fang et al. 2017). Other latent safety measures are available, but are used only in specific contexts (e.g. for fleet vehicles) or not at all. These include alcohol ignition interlocks and speed governors (Elder et al. 2011).

Notably, it is possible that drivers become less attentive or drive differently because safety measures that assume parts of the driving task on their behalf according to risk compensation theory (Hedlund 2000). Hedlund writes that there are four factors that influence risk compensation: visibility, effect, motivation, and control (2000). To limit or eliminate risk compensation behaviors, latent measures should rate low on at least one of the aforementioned factors in order maintain some level of active engagement from road users (Hedlund 2000). For example, by implementing measures that people are not aware of because they are not visible (e.g. roll cages), it is less likely that one will change behavior in response to it.

Beyond the vehicle itself, there are other latent safety measures that may be used to alter risk of crashes and injuries. Automated vehicle enforcement via speed cameras has been shown to reduce overall vehicle speeds (Pilkington and Kinra 2005; Richter et al. 2006). Unlike in-person enforcement, this does not require individual decision making from a police officer to choose who might be ticketed and cited. Further, when the location of speed cameras is known and obvious, they can have a preventive effect by encouraging drivers to slow down in the first place. Further, automated enforcement can help shift the speed curve, rather than target only the worst offenders, increasing population health impact (Richter et al. 2006, Wilson et al. 2010).

Active measures

Next, we replace “Clinical Interventions” (Tier 4 in Figure 2 and Table 3) with “Active Measures.” Active measures are those that are highly effective, act at the individual level, and require a great deal of individual effort. This tier combines the PPE and engineering controls from the Hierarchy of Controls. Active measures such as seat belts, motorcycle and bicycle helmets, and turn signals have been widely deployed in transportation safety, but their health benefit is contingent on individual users (Robertson 1976; Evans and Frick 1988; Cummings, Wells, Rivara 2003; Liu et al. 2008). Other active safety measures are available such as forward, rear, and side collision *warnings* alert drivers to hazards, but require drivers to take evasive maneuvers. One might also consider high-visibility apparel for people walking or cycling as active measures as they can increase visibility but require individual effort. In-person enforcement is also an active measure as it requires individual officers to make decisions about who is speeding. Further, in-person enforcement can negatively influence other aspects of health, including traffic safety when traffic safety enforcement is used as a means of profiling Black people, and other persons of color (Novak and Chamlin 2012). Routine traffic stops have frequently led to violence perpetrated against the Black population, eroding trust in government institutions and potentially traffic safety in general (Novak and Chamlin 2012).

Education

At the top of the health impact pyramid is educational interventions (Tier 5 in Figure 3 and Table 1). This tier is missing in the Hierarchy of Controls, but might be codified under "Administrative Controls." Regarding behavioral approaches, Frieden writes "The need to urge behavioral change is symptomatic of failure to establish contexts in which healthy choices are default actions" (Frieden 2010). This applies to public health generally and transportation specifically. If one needs to constantly remind people to slow down, stop at red lights, or yield to pedestrians, it is necessary to examine the scenario to determine whether the socioeconomic context or built environment encourage risky behavior. If altering these contexts is not possible, then applying passive or active measures should be explored. However, education interventions tend to be the least politically controversial, least expensive, and easiest to implement. Educational interventions can thus contribute to traffic safety programs by raising awareness of new policies (e.g. a speed limit change), promoting safety as a cultural value, helping people navigate the transit system or try walking and cycling, and as a means of teaching the rules of the road. Educational measures can be important and effective when they are complementary to other approaches and combined with efforts from other tiers in the pyramid.

DISCUSSION

Gibson, Gordon, Haddon and others worked to understand the first principles/causes of injuries. This is foundational in understanding how to prevent injuries by understanding the different factors that might contribute to traffic injuries. Using these theories, we have come to understand that the agent of injury is kinetic energy and that approaches to prevent or control its transfer to human bodies must be used to prevent injuries. Understanding the etiology of traffic injuries is important for understanding how to eliminate them. Further, the public health principles of prevention, and population level interventions will help prevent serious and fatal injuries.

The traditional tools and frameworks used to evaluate Vision Zero and other traffic safety programs inadequately describe the complexity of the road safety problem and attribute outsize effectiveness to behavioral interventions and falsely assign blame to individuals in the roadway environment. The Federal Highway Administration's guidance on safety planning promotes the E's framework as a means of implementing Safe Systems and Vision Zero programs (Tang et al. 2018). The "E's" framework suggests a false equivalence between different countermeasures, does not incorporate public health principles of prevention and population level intervention, and does not focus on the agent of injury: kinetic energy.

By using the Safe Systems Pyramid to evaluate Vision Zero and other traffic safety programs more broadly, practitioners can prioritize countermeasures by their effectiveness in controlling or preventing the transfer of kinetic energy, assess the population level impact, determining whether individual effort is needed, and support efforts that address the social determinants of health. The Safe Systems Pyramid is thus an “Intervention” public health model to prioritize health policies. This pyramid builds on the work of Haddon and other injury control researchers by linking transportation practice to public health thinking and strategy. Although public health engineering is no longer its own discipline, incorporating public health theories can assist engineers and other professionals working on the built environment to apply public health methods.

Codifying and prioritizing interventions in the health impact pyramid does not mean that only one approach is needed. Rather, the pyramid structure is intended to help engineers and other road safety practitioners understand the population health impact of various interventions. No single strategy can be effective alone. When various preventive measures are used in combination, and to the extent that they influence social norms and cultural factors, they can be more effective than interventions affecting individuals alone. Vision Zero and the Safe Systems approach call for a paradigm shift in transportation safety. To induce such a shift, it is necessary for transportation professionals to understand their roles as public health professionals and incorporate public health principles into their thinking and practice. The Safe Systems Pyramid provides a framework for such thinking.

CONCLUSIONS

Traffic safety is a public health problem that requires public health strategies and approaches. The principles of injury prevention and control are long established in public health but have been neglected as a means of developing transportation policy. By incorporating the principles of injury prevention and control into the Health Impact Pyramid, transportation engineers and other professionals can better understand the problem of traffic injuries and work to prevent them.

The Safe Systems Pyramid is of interest to transportation engineers, planners, policymakers, and educators. Professionals that influence the built environment influence health. The increasing awareness of the influence of transportation on public health outcomes, and calls for collaboration between transportation and public health practice are important. However, awareness and collaboration are limited. Transportation professionals lack formal public health training and are unlikely to apply public health ideas systematically or intentionally, even if they share the values of public health practitioners. Frameworks can help professionals bridge gaps between science, values, and practices. The Safe Systems Pyramid can be used to influence and prioritize interventions and policy as well as an educational tool to help transportation professionals adopt a public health consciousness.

Public health practice is founded on the ideas that health problems are preventable, should be addressed at the population level, and that one should focus on preventing and controlling risk factors while promoting protective factors when possible. These principles are inherent in Safe Systems and Vision Zero policies, which emphasize that deaths are preventable, and that speed is a primary risk factor. These ideas are present in many Vision Zero plans and policies in the US (Fleisher, Wier, and Hunter 2016). However, these policies lack a simple, cogent framework for prioritizing interventions based on the science of injury prevention and control. By incorporating elements of population health principles from the Health Impact Pyramid and control strategies from the Hierarchy of Controls, the Safe Systems Pyramid codifies the public health principles underlying transportation safety practice.

Engineers have played an important role in public health for centuries, from building sewer systems, to draining swamps, to building safer vehicles. The science and values of public health were foundational to that work. Similarly, the principles and science of injury prevention and control are foundational to the work of transportation engineers and planners. The Safe Systems Pyramid is a means of bridging the public health principles inherent within the Safe Systems approach with everyday transportation decisions.

CHAPTER 3 APPLYING THE PUBLIC HEALTH APPROACH IN GEORGIA

A key function of public health is to identify the incidence and prevalence of a particular health condition and its risk factors. In the public health literature, this is referred to as "surveillance." Surveillance was formally defined by the World Health Assembly in 1968 using three main features:

1. The systematic collection of pertinent data,
2. The orderly consolidation and evaluation of these data; and
3. The prompt dissemination of the results to those who need to know, particularly those who are able to take action.

Surveillance data on disease outcomes is commonly reported. However, risk factor surveillance is another key function for public health. For example, the Centers for Disease Control and Prevention maintains the Behavioural Risk Factor Surveillance System (BRFSS). The BRFSS does not track specific cases or instances of diseases, but only those behaviours that might be related to adverse conditions, such as sedentary behaviour or poor diets.

Departments of Transportation typically maintain crash databases, which typically meet the definition of a public health surveillance system. Less common, however, is continuous surveillance of crash risk on the roadway, noting where risk factors for crashes and injuries are *most likely* to occur. New technologies allow for continuous collection of data relevant to roadway safety: cell phones collect precise location data, and high-resolution cameras collect data on vehicle movements. These new data sources will allow for passively collected information on roadway risks.

Risk factor surveillance can thus supplement network screening. In developing a performance metric based on crash risk, transportation professionals can implement a key method of public health surveillance in their work. Risk factor surveillance systems act as a “first warning” system for where a particular outbreak might occur or condition may become prevalent. In transportation safety, “hotspotting” is typically used to identify where dangerous areas of roadway are located and to prioritize safety projects. With speed data available at the network level, departments of transportation can also monitor risk factors for traffic crashes and injuries by monitoring speed at the network level.

LITERATURE REVIEW ON VEHICLE SPEED AND SAFETY RESEARCH

Vehicle speed is a widely studied topic in transportation safety. However, hypotheses on the relationship between speed and crashes frequently contradict one another (Shinar 1998). For example, some studies suggest that traveling at lower speeds is associated with a decreased risk of crashing (Elvik et al. 2019), while others claim that low vehicle speeds may be associated with increased risk of crashing (Solomon 1964). When studying speed, it is important to clarify whether one is interested in the nature of this relationship at the individual driving level or at the aggregated traffic level. At the individual level, increased driving speed is associated with increased braking distance and increased severity of injury should a crash occur (Elvik et al. 2019).

In this review, we focus on the relationship between aggregated operating speeds on roadways and crash frequency. This relationship has been the subject of several research studies, but its precise nature is still debated. In this chapter, we provide an overview of the research on aggregated speeds and crash frequency, as well as the statistical models used to evaluate this relationship. In addition, this review includes research on key mediating factors between operating speed and crash frequency, such as speed limits and roadway characteristics. We also include separate sections on the relationship between speed and safety for pedestrians and cyclists, i.e., vulnerable road users, as speed is an especially important factor for crashes involving these groups.

Theories on Speed and Crash Frequency

Several hypotheses have been made about the nature of the relationship between speed and crash frequency. One of the most widely cited studies on the relationship between vehicle speed and crash frequency in the United States was conducted by David Solomon on rural roads in 1964. Solomon's study posits that there is a U-shaped relationship where crashes are most likely to occur at the highest and lowest speeds (Solomon 1964). More recent research on the speed–crash relationship suggested that there is a power/exponential relationship between speed and likelihood of crashing (Elvik et al. 2019). The relationship between the mean travel speed (i.e., operating speed) and likelihood of injury has frequently been studied (Aarts and van Schagen 2006, Elvik 2005, Elvik 2013, Elvik et al. 2019, Nilsson 2004, and Shinar 1998). Despite the many studies on the topic of speed and safety, speed measurement has not been incorporated into regular performance management practices. The next sections primarily focus on the different theories about the relationship between aggregated vehicle speed and risk.

Solomon's Curve

The U-shaped curve was proposed as the prevailing relationship between speed and crash rates as early as the mid-20th century by David Solomon (1964). This model suggests that there is a traffic speed that minimizes collisions, and that large deviations from that speed tend to increase collision risk (Solomon 1964). The “Solomon’s curve” presented in figure 4 is based on Solomon’s analysis of two- and four-lane rural highways in the 1950s.

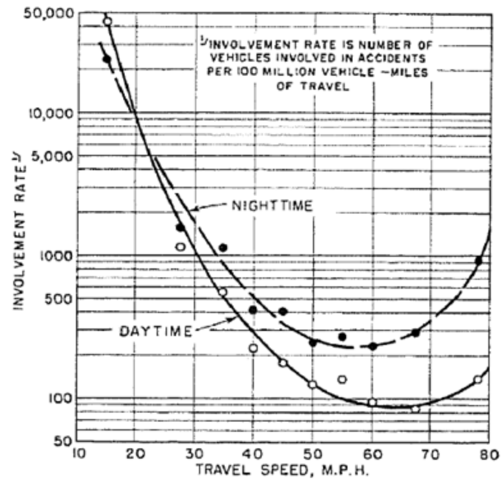

Figure 2.—Involvement rate by travel speed, day and night.

Figure 4. Line graph. Solomon’s curve of the relationship between crash rate per 100 million vehicle miles traveled and travel speed (Solomon 1964).

This theoretical model has been prevalent in transportation engineering for decades and continues to be referenced today. For example, Solomon’s curve is featured in the *Highway Safety Manual* (HSM), Federal Highway Administration (FHWA) guidance on changing speed limits, and state-level speed limit guidance (Parker 1997, AASHTO 2014, Tennessee Department of Transportation 2019). Although “A Policy on Geometric Design of Highways and Streets” does not explicitly cite Solomon, it references his thesis on deviations from speed being dangerous:

> *“Crashes are not related as much to speed as to the range in speeds from the highest to the lowest. Regardless of the average speed on a main rural highway, the greater a driver’s deviation from this average speed, either*

lower or higher, the greater the probability that the driver will be involved in crashes" (AASHTO 2011, p. 2-83).

Notably, very low-speed crashes account for less than 1 percent of the crashes in Solomon's study. The relationship between speed and safety at higher speeds in Solomon's study is far more precise. In Figure 1Figure 4 above, a few observations of crashes below 10 mph heavily skew the crash rate at low speeds. Most speeds in Solomon's study were above 45 mph (Solomon 1964). Although the weaknesses of Solomon's study have been pointed out, it continues to be cited today. However, it is increasingly assumed that higher speeds are associated with more and more severe crashes.

Power and Exponential Models of Speed and Crashes

Using the Newtonian equations for kinetic energy, researchers developed an empirical model relating mean operating speed to the number of crashes on a typical roadway using a power model (Nilsson 2004). This model states that the increase in the number of crashes is proportional to the increase in operating speed. Nilsson's power model uses the general functional form shown in figure 5.

$$\boldsymbol{Accidents_{after} = Accidents_{before} \times (\frac{speed_{after}}{speed_{before}})^{exponent}}$$

Figure 5. Equation. Nilsson's power model of changes in speed and crashes.

In the equation in figure 5, Nilsson describes a relationship before and after a change in speed. Should a change in aggregate operating speed occur, Nilsson posits that the change in crashes is proportional to the ratio of the change in mean speeds. The exponent on the ratio of average speeds before and after depends on the severity of injuries being calculated. Nilsson's power model can, thus, be fitted for different crash severities and road types. The power model has been studied repeatedly and is frequently used as a baseline estimate for safety performance functions (Elvik 2005).

The exponential model has been suggested as more appropriate than a power model for studying the relationship between speed and safety (Hauer 2009). The exponential and power models are very similar, but they differ in one key aspect: the power model suggests that the relationship between speed and safety does not depend on the initial speed, while the exponential model does. The proposed exponential model is given in figure 6, where *Y* denotes crashes and *v* denotes speed, subscript 1 after a change in speed and subscript 0 before a change in speed.

$$\boldsymbol{Y_1 = Y_0 e^{(\beta(v_1 - v_0))}}$$

Figure 6. Equation. Exponential model of speed and crashes.

In other words, the power model assumes that a speed reduction from 30 mph to 20 mph provides the same benefit as a reduction from 70 mph to 60 mph. Conversely, the exponential model suggests that the magnitude of the change in crashes after decreasing from 70 mph to 60 mph would be larger than the change after decreasing from 30 mph to 20 mph.

In response to these criticisms, Elvik (2013) updated his power model to use a continually varying coefficient depending on the severity of the injury. Elvik's updated power model of speed and safety is a set of six equations: one each for deaths, fatal and serious injuries, and all injuries, and then three for the number of crashes in each of those categories, respectively. The general form of the model remains the same, as in the equation in figure 7; however, the exponent *x* varies from 2 to 6, depending on whether the user is estimating all crashes, injury crashes, or fatal crashes.

$$\boldsymbol{Y_1 = (\frac{V_1}{V_0})^x Y_0}$$

Figure 7. Equation. Generalized power model for speed and crashes (Elvik 2013).

To model overall injuries, Elvik proposed adding a second term, *Z*, to represent the number of people injured or killed before and after a change in speed. The model, thus, becomes as the equation in figure 8.

$$\boldsymbol{Z_1 = (\frac{V_1}{V_0})^x Y_0 + \left(\frac{V_1}{V_0}\right)^{2x} (Z_0 - Y_0)}$$

Figure 8. Equation. Power model for speed and injuries (Elvik 2013).

The model can, thus, be used to estimate the total change in injuries or injury crashes relative to a change in speed. Elvik's model suggests that there is a clear "dose–response" relationship between speed and road safety. The larger the "dose" of the speed, the larger the increase in potential injuries. This updated power model is slightly different than Elvik's initial conception, with specific values for each exponent, as described in table 3. Other studies focused more on the roadway context instead of solely speed. In those cases, increases in average speeds differed depending on the class of roadway, with increases in operating speeds increasing risk more on lower roadway classifications relative to higher roadway classifications (Elvik, Christensen, and Amundsen 2004; Nilsson 2004).

Table 3. Elvik's estimates for the power model estimating the relationship between operating speed, crashes, and injuries (Elvik 2013).

Accident or injury severity	exponent	interval
Fatalities	4.5	(4.1 – 4.9)
Seriously injured road user	3.0	(2.2 – 3.8)
Slightly injured road user	1.5	(1.0 – 2.0)
All injured road users (severity not stated)	2.7	(0.9 – 4.5)
Fatal accidents	3.6	(2.4 – 4.8)
Serious injury accidents	2.4	(1.1 – 3.7)
Slight injury accidents	1.2	(0.1 – 2.3)
All injury accidents (severity not stated)	2.0	(1.3 – 2.7)
Property-damage-only accidents	1.0	(0.2 – 1.8)

Source: TØI report 740/2004

Many studies that examined the effect of average operating speed on a roadway concluded that crash rates increased as operating speeds increased (Aarts and van Schagen 2006). This relationship between speed and crashes can be described using several mathematical models, but the most prevalent are power and exponential functions (Finch et al. 1994; Nilsson 1982, 2004; Elvik et al. 2019).

Speed Variation and Safety

Speed variation is another measure of speed cited as a predictor of crashes on specific roadway links (Solomon 1964, Lave 1985). Speed variation is frequently assessed using the standard deviation or coefficient of variation of a speed distribution (Taylor, Lynam, and Baruya 2000). These studies suggested that if there is a large standard deviation in speeds, there is likely to be more crashes on a roadway link. However, the magnitude of the relationship between standard deviation and increased probability of crashing is difficult to quantify or interpret in real-world scenarios. Other metrics of speed variation or dispersion have been studied, such as the variance (Kweon and Kockelman 2005).

Studies that have found a positive relationship between speed variance and crashes often found that there is a negative relationship between average speed and crashes (Lave 1985). Lave's analysis examined the relationship between speed and number of crashes on urban and rural interstates, arterials, and collectors. In each of 12 different regressions, speed variation was significantly related to increased crashes. None of the models with average speed found a significant relationship between average speed and risk of crashes. In fact, in 10 of the 12 regression models, the coefficient on average speed and crashes was negative. Similar to the proposed analysis, Lave used annual speed variation and measures of central tendency. Further, Lave's analysis concluded that changes in speed variation are symmetric across the speed distribution. Under this assumption, an increase of 1 mph in mean speed is equal to a 1-mph decrease in the 85th percentile speed in terms of expected safety outcomes. Lave's conclusion that "variance kills" rather than speed kills, and his suggestion to enforce low speeds (to reduce variance) led several other researchers to reanalyze Lave's data (Levy and Asch 1989, Fowles and Loeb 1989, and Snyder 1989). One of the main criticisms was that Lave's research did not consider the joint effect of speed and speed variance, and a singular focus on increasing average speed to decrease variance. In response to Lave's analysis, Levy and Asch (1989) used the difference between 85th percentile and mean speed, as well as an interaction between mean speed and the difference. Levy and Asch, thus, concluded that speed itself is important, but through its interaction with speed variance.

Shefer and Reitveld (1997) posited that when average speed is held constant, speed variance increases risk, and when variance is held constant, increasing speed increases risk. When both mean speed and variance increase at the same time, risk still increases, but the potential contribution of speed variation to risk decreases. Thus, risk still increases, but the marginal effect of the increase in average speed decreases. This argument is presented from Figure 2a of Shefer and Reitveld (1997) in figure 9.

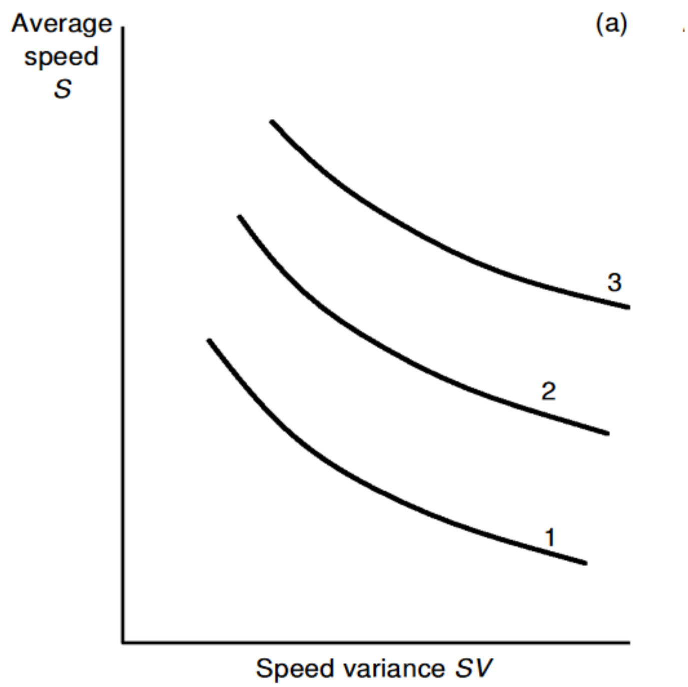

Figure 9. Line graph. Relationship between average speed and speed variance (Shefer and Reitveld 1997, Figure 2a).

Roadway sections with large variations in speed may be indicative of high congestion and low speeds during peak hours, but low congestion and high speeds at other hours. Areas with lower traffic may have more variation in speed but simply have fewer vehicles present on the roadway. Speed variance may capture information on roadways that are built specifically for high congestion conditions, but function poorly at all other times of day. This hypothesis is supported by several studies that found that areas with high speed variances tended to have lower average speeds (Garber and Gadiraju 1989; Taylor, Lynam, and Baruya 2000). Roadways with higher average speeds also tended to have less variation in speeds in both studies. As with other areas of speed research, the functional class and context of the roadway are important when considering speed variance. The effect of speed variance is likely different across different functional classes of roadways.

Taylor, Lynam, and Baruya (2000) proposed a theoretical relationship between speed, speed variance, and safety, noting that both speed and speed variance are related to safety outcomes and should be accounted for in an analysis or performance metric (see figure 10). Taylor's conceptual framework noted that infrastructural and traffic flow characteristics influence a driver's speed choice and, thus, influence the speed distribution (Taylor, Lynam, and Baruya 2000). In addition, Taylor also pointed out that other factors, such as weather or lighting, influence crash frequency. Notably, Taylor posited that measures of average, spread, and percentage of those exceeding the speed limit on a roadway link influence crash frequency jointly. Thus, Taylor concluded that multiple metrics should be considered together when evaluating safety through speed performance measurement.

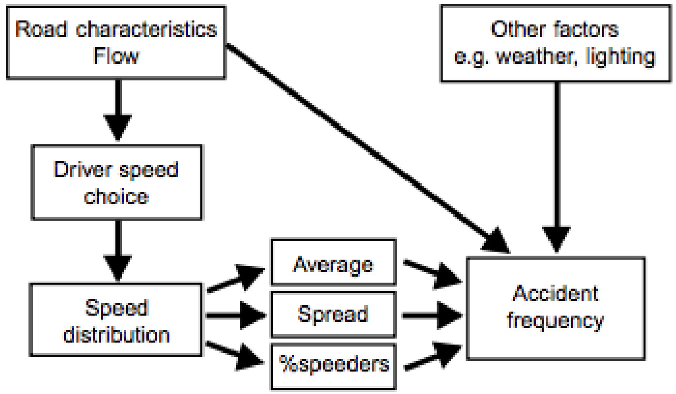

Figure 10. Flowchart. Taylor's conceptual model relating road characteristics and speed-based performance metrics to safety outcomes (Taylor, Lynam, and Baruya 2000).

Considerable theoretical and quantitative evidence exists to suggest that speed variance influences crash frequency, and that increasing variation in speeds is likely to result in more crashes. However, high speeds are naturally more likely to be severe should a crash occur. It is reasonable to suggest that the relationship between speed and crash frequency is likely influenced by the spread of speed as well as the overall operating speed.

Crash Count Modeling Techniques

Crash modeling techniques continue to develop today. Linear models have long been shown to be inadequate, since crash outcomes are discrete and at least zero. As a result, Poisson and negative binomial (NB) models have long been the standard for estimating crash frequency (Lord, Washington, and Ivan 2005). The NB model is generally preferred, because the Poisson model makes a restrictive assumption that the dependent variable is not overdispersed (i.e., its variance is greater than its mean). In the case of unlikely, random events such as crashes, the NB model offers welcome freedom from that restriction (Lord, Washington, and Ivan 2005).

Crashes are relatively rare events, and depending on the unit of analysis, many observations may have zero crashes. Zero-inflated negative binomial (ZINB) models have become popular for this kind of data. These models break out observations with zero crashes from observations with at least one crash, modeling them separately (Lord, Washington, and Ivan 2005). ZINB models have shown improved fit compared to NB models in some cases, because aggregated crash data frequently come with a preponderance of zeros. However, they come with an important caveat: ZINB models assume separate models for observations with and without crashes. The distribution for observations with zero crashes suggests that there is an "unsusceptible" population. This distribution is not derived from the distribution of all observations (i.e., including those with crashes, or the "susceptible" population), but is an assumed distribution based on only those observations without crashes. Some researchers have considered ZINB models with some skepticism because of this assumption (Lord, Washington, and Ivan 2005).

More recently, Bayesian methods have grown more popular, and are the standard according to the *Highway Safety Manual*. A advantage of Bayesian methods is their ability to account for the prior distribution of crashes and other key covariates to avoid for regression to the mean bias. Thus, Bayesian methods can account for an important source of variation found in crash data (Aguero-Valverde and Jovanis 2006, Quddus 2008, Chen 2015). Several studies have compared naive models to Bayesian models and found that the latter had significantly greater explanatory power in modeling coefficients related to crash frequency (Quddus 2008; Siddiqui, Abdel-Aty, and Choi 2012). Importantly, Quddus (2008) found that when comparing naive models to Bayesian, most variable coefficients were similar, except for the coefficient for average speed. Notably, Bayesian methods have become the new standard for modeling crashes at the area level (Hauer et al. 2002).

Tasic, Elvik, and Brewer (2017) proposed the generalized additive model (GAM) for modeling crashes to account for spatial correlation in crash data. They argued that the modeling process' key advantage is being simpler and less intensive than Bayesian counterparts.

Speed Limits and Safety

One of the primary means of speed control in the United States is the setting and enforcement of speed limits. Speed limits can ensure that drivers operate at a prudent and safe speed. The Uniform Vehicle Code (UVC), a set of model traffic laws, recommends establishing uniformity in roadway contexts by setting similar speed limits on roads that are physically similar (Forbes et al. 2012). Speed limits are both posted and statutory, i.e., municipalities set a default speed limit if the limit is not posted. Most states create engineering design guidelines to prescribe specific ranges for speed limits (e.g., 25–45 mph for urban arterials), and geometric designs for specific functional classes (e.g., urban arterials may have a 25–45 mph speed limit and two to four lanes) (Forbes et al. 2012). The posted speed limit is sometimes changed using an engineering study, expert system, or because of a "special" situation such as a school zone (Forbes et al. 2012). Outside of those special cases, there tends to be some degree of similarity between roadways with the same or similar speed limits. Many geometric design elements, such as horizontal curvature, are influenced by the intended design speed, which in turn informs the posted speed limit (Fitzpatrick et al. 2001). As many design elements are based on the design speed, the posted speed limit tends to accurately predict the operating speed on a given roadway (Fitzpatrick et al. 2001, Dixon et al. 2008, Wang et al. 2006).

The relationship between posted speed limits and safety continues to be investigated. Much of the research on speed limits is related to changes in speed limits and whether a change in crashes occurs after the speed limit is changed (Castillo-Manzano et al. 2019; Elvik 2013; Elvik et al. 2019; Heydari, Miranda-Moreno, and Liping 2014; Hu and Cicchino 2020; Kockelman et al. 2006; Silvano and Bang 2016).

Elvik and Vaa (2004) analyzed the results of 52 studies from 1966 to 1995 and concluded that a reduction in speed limit was associated with reduced numbers of fatal and injury crashes, with a larger decrease in fatal crashes. Elvik et al. (2019) revisited the topic again in 2019, reviewing 97 studies that analyzed changes in crashes and injuries related to changes in posted speed limits. Notably, Elvik's research on speed limit changes was specific to areas that changed speed limits without a change in built infrastructure (Elvik 2013; Elvik et al. 2019). A study of disaggregated speed and collision data on high-speed roads (i.e., speed limits 55 mph or above) estimated that a 10-mph increase in speed limit is related to a 3-mph increase in average operating speed (Kockelman et al. 2006). Similarly, decreases in speed limits do not have a one-to-one relationship with decreases in speed. A 2016 Swedish before–after study showed that a 10-km decrease in speed limit resulted in a 1.57-km decrease in speed (Silvano and Bang 2016). In addition, other studies found that the mean operating speed may not change, but the higher end of the speed distribution (e.g., 95th percentile speed, or those exceeding the speed limits by 20 mph or more) decreases after speed limits are lowered (Silvano and Bang 2016, Hu and Cicchino 2020). Differences in responses to speed limits may be related to where roads are located. NCHRP 504 notes that nearly all vehicles operating on rural roadways tend to be within 10 mph of the speed limit, while urban and suburban roadways have 5–10 percent of vehicles operating at speeds outside those bounds (Fitzpatrick et al. 2003). Thus, many analyses have found that average operating speeds tend to change after changes in speed limits. However, the magnitude of rate of change depends on the functional classification of the roadway, the context of the roadway, and local conditions that might influence speed.

Infrastructure, Speed, and Safety

The built environment and other vehicles on the roadway influence both the speed and the frequency of crashes. Several characteristics of the roadway and traffic flow are typically included in crash frequency studies. Intuition and significant research indicate that the interaction among drivers and between drivers and their immediate environment greatly influence the chances of a crash. Here, we briefly review some of the key factors that influence both speed and crash frequency.

In addition to speed limits and other traffic control devices, the *Highway Capacity Manual* (HCM) notes the speed of vehicles on urban streets is influenced by factors in the road environment (AASHTO 2014). These factors include number of lanes, lane width, shoulder width, surface type, access density, presence of cyclists and pedestrians, and land use (Ottesen and Krammes 2000, Fitzpatrick et al. 2001, Ewing and Dumbaugh 2009, Ben-Bassat and Shinar 2011, Marshall and Garrick 2011, Gargoum and El-Basyouny 2016).

Many design features are dictated by the speed limit and functional class of the roadway. For example, an urban arterial may be more likely to have a lower speed limit than a rural arterial, and thus fewer and narrower lanes. It is difficult to disaggregate the effect of specific features from the posted speed from the functional class (Gattis and Watts 1999). However, evidence suggests that different design elements have a marginal effect on speed, although it is generally less than speed limit or functional class.

Horizontal Curvature

One of the key horizontal design criteria for influencing speed is curve radius. As the radius of a horizontal curve increases, speed increases (Poe et al. 1996, Fitzpatrick et al. 1995, Fitzpatrick et al. 1999, Fitzpatrick et al. 2001). In addition to the curve radius, the deflection angle of a horizontal curve may influence speed as much as or more so than the curve radius on suburban and urban roadways (Fitzpatrick et al. 2001, 2003). Fitzpatrick et al. (2001) posit that deflection angle may explain more variation in speeds because drivers may be more sensitive to the appearance of a curve rather than the perceived comfort of the curve.

Lane Number and Width

In general, roadways with more lanes exhibit higher speeds (Fitzpatrick et al. 2001; Dumbaugh and Li 2010). When more lanes are available, drivers may choose to drive at higher speeds, as an increased number of lanes allows drivers to sort themselves by speed (Dumbaugh and Li 2010).

Narrower lanes are associated with lower speeds (Fitzpatrick et al. 2001, Ewing and Dumbaugh 2009, Dumbaugh and Li 2010). Simulator studies suggest that lanes that are physically narrower or appear narrower because of street trees or other roadside elements exhibit slower speeds (Gattis and Watts 1999; Naderi, Kweon, and Maghelal 2008). However, as the overall width of a roadway increases, the effect of lane widths on speed decreases (Gattis and Watts 1999). The width of the roadway, whether right-of-way width or number of lanes, may also be a factor in explaining active transportation crashes. This element of the roadway may affect the bicyclist or pedestrian’s ability to judge a safe crossing or turn, as well as having an influence on vehicle speeds (Ma et al. 2010). Ukkusuri et al. (2012) found that the number of lanes was positively associated with pedestrian crash frequency, and that right-of-way width was less effective at explaining crash frequency.

Access Density

As the number of access points (e.g., driveways, intersections) increases on a roadway, speeds tend to decrease (Fitzpatrick et al. 2003). With more intersections and driveways, the potential for drivers to turn into or out of the stream of traffic increases. These movements tend to slow traffic down as the driver prepares to turn out of the stream of traffic or enters the stream of traffic. Thus, a disproportionate number of crashes may occur at lower speeds as the potential for conflicts increases (Fitzpatrick et al. 2003). An increase in crashes at low speeds may be a function of conflict density rather than speed itself. Access density is frequently related to land use, as denser commercial and residential land uses tend to increase the number of driveways and intersections and are associated with decreasing speeds (Ewing and Dumbaugh 2009; Marshall and Garrick 2011).

Traffic volume, intersection density, and roadway functional class are often included as controlling variables in studies that estimate expected crash frequency. Greater traffic volume leads to increased potential conflict, both among vehicles, and between vehicles and active transportation users (Kaplan and Prato 2015). Some of the earliest speed and safety studies did not control for traffic volume, leading to erroneous results (Baruya 1998, Dumbaugh and Rae 2009).

Congestion and Safety

Congestion, vehicle speed, crash frequency, and crash severity have a complex relationship. Intuitively, congestion and vehicle speeds are negatively correlated. Less congested roadways allow people to drive at high speeds. However, when roads are more congested, there are more vehicles on the roadway and, thus, a higher number of persons exposed to potential crashes and injuries. Research on the relationship between congestion and safety is mixed, with no accepted relationship (Shefer and Rietveld 1997; Zhou and Sisiopiku 1997; Kononov, Bailey, and Allery 2008; Wang, Quddus, and Ison 2013; Albalate and Fageda 2019; Retallack and Ostendorf 2020). Some research suggests that congestion improves safety by decreasing severe crashes (Shefer and Rietveld 1997), while other research notes that safety decreases with increasing congestion (Kononov, Bailey, and Allery 2008). Similar to the speed and safety relationship, it has been hypothesized that there is a "U-shaped" relationship, where the likelihood of crashes is highest at low and high congestion, with relatively fewer crashes around average congestion (Zhou and Sisiopiku 1997), while other evidence suggests that there is no relationship between the level of congestion and safety (Wang, Quddus, and Ison 2009; Quddus, Wang, and Ison 2010).

There is general agreement that increased congestion is related to lower speeds, and lower risk of fatal crashes exists during the congested traffic state (Zhou and Sisiopiku 1997, Ivan et al. 2000, Martin 2002). However, most of these analyses of congestion are conducted on highways, and the relationship between congestion and safety on urban and rural arterials is less clear. Congested roadways, by definition, have a high number of vehicles for the allotted space. However, congested roadways also move more slowly. Thus, it is difficult to state whether congestion itself influences crash risk.

Network Screening for Safety

In transportation, the process of analyzing a particular roadway and identifying where dangerous areas are located is referred to as "network screening" (Hauer et al. 2002). The simplest and most common form of network screening is "hotspotting," where the locations with the most crashes over a defined period of space and time are identified and prioritized for safety improvements (Montella 2010). There are several methods of hotspotting, including comparing crash frequencies, crash rate per vehicle volume, and empirical Bayes estimates (Cheng and Washington 2008, Montella 2010). Hotspotting is widely used amongst state and local departments of transportation to prioritize safety investments (Persaud 2001, Elvik 2007, Montella 2010). Crash data are regularly collected and available, making these estimates relatively easy to calculate. However, hotspotting identifies risk after crashes have occurred. Many surrogate safety measures have been proposed to proactively identify risk or supplement hotspotting methods (Moreno and García 2013; Laureshyn et al. 2017; Tarko 2012, 2018). Surrogate safety metrics tend to be used to evaluate specific intersections (e.g., those with cameras to record traffic) or evaluate projects before and after implementation (Tarko 2012, 2018).

In addition to full network screening, speed data may be used to evaluate particular roadway links or segments to suggest revision in infrastructure or speed limits. For example, the FHWA's USLIMITS2 web-based tool and the National Association of City Transportation Officials' (NACTO) *City Limits* guidance both use several metrics of speed in addition to infrastructure characteristics (FHWA 2019, NACTO 2020). The FHWA's "Methods and Practices for Setting Speed Limits" informational report reviews several speed study methodologies and notes that several percentile speeds should be collected, and that "the safest conditions occur when all vehicles at a site are traveling at about the same speed" (Forbes et al. 2012).

Safety performance metrics are most useful when they can be applied and analyzed to determine where intervention is needed. In addition to defining the relationship between a risk factor and an outcome, it is important to put the performance metric into use via a regularly reported program.

Summary

A review of the literature revealed that more research is needed to understand the impact of vehicle speeds on safety. Some factors are clearly related to increased crash frequency—traffic volume, congestion, roadway characteristics, population density, and bicycle/pedestrian activity. In addition, land use characteristics have been shown to be critical factors, including higher traffic volumes and increased intersection density. In general, these same factors are related to increases in crashes involving pedestrians and cyclists should they be present on a given roadway link. Finally, increasing speed is related to increases in crashes and is becoming more prevalent. However, there is less agreement on how to best measure speeds for safety performance. Until recently, most speed studies relied on a limited set of speed data from corridor-level and instrumented vehicle studies. With increasingly available operating speed data reported on surface roadways, the relationship between operating speed and crash frequency is an important area of research.

CHAPTER 4 METHODOLOGY FOR ASSESSING RELATIONSHIP BETWEEN PROBE VEHICLE SPEEDS AND CRASHES

The primary purpose of this research was to investigate the relationship between annual operating speeds on nonhighway roadway segments, and determine whether and how operating speed data could be used for performance measurement. To assess these relationships, we used negative binomial models with the number of annual crashes per year as the outcome variable, with various measures of operating speed as the independent variable of interest.

Due to the large size of the speed data set, and the multiple data sources that needed to be conflated to the roadway network, we first tested the conflation and statistical modeling process on one corridor: Georgia State Route 6. We present these results first, followed by the analysis of the full roadway network.

In the initial case study of Route 6, we include estimates of traffic volumes, number of lanes, and length of TMC as control variables. We added further covariates in models of the full network and changed the specification of some covariates to adjust for the larger variation in roadway types and contexts. We included the same set of covariates in all models of the full network, including measures for traffic volume, land use context, geographic region, and length of the roadway segment. The specifications for the State Route 6 analysis are specified slightly differently than those presented for the full network. NB coefficients for continuous variables are interpreted as changes in the log count of the outcome variable. Thus, the signs of coefficients are similar to those in linear regression, but calculating expected changes requires exponentiating the coefficients to determine expected counts from models.

Because the purpose of the research was to create performance metrics based on speed, we also modeled the relationship between operating speed and crashes on subsets of the data to determine whether the relationships were the same in different scenarios. For example, we segmented the speed and crash data to specific hours of the day to examine whether the speed–crash relationship differs between peak hours with congested roadways and off-peak hours when traffic may be at free flow.

The data used in this analysis came from four different data sources, as follows:

- The GDOT Georgia Electronic Accident Reporting System (GEARS) crash database supplied crash data for the years 2013–2017; these data were processed and provided by GDOT.
- The National Performance Management Research Data Set (NPMRDS n.d.) furnished probe vehicle speed data. These data were obtained, consolidated, processed, and maintained by INRIX, Inc. and were accessed for this study via a GDOT data-use license. In addition to the probe vehicle speed data, this data set includes data on roadway traffic volume, number of lanes, and functional class. INRIX began providing speed data for NPMRDS in 2017; thus, 2017 was the only calendar year with complete data for this analysis.
- GDOT provided speed limit data.
- The U.S. Environmental Protection Agency (EPA) website offered ecoregion data, which we downloaded directly from the website.

In the following sections, we describe these data sources in detail, and then outline the methods used to prepare the final data set. After describing the data and the processes for data preparation and conflation, we discuss the modeling method and why different control variables were included in the analysis.

CRASH DATA

The GEARS crash database is an exhaustive collection of crash records submitted in the state of Georgia. This database is web-hosted, and an end user can query the database to access crash records by date, time, jurisdiction, vehicle type, and other key information provided on the crash record.

GDOT also creates and maintains a spatial dataset of crashes, which has been preprocessed for spatial analysis. The spatial dataset was the primary crash resource used in this analysis, but direct data pulls from GEARS were used to backfill and verify the preprocessed data set.

SPEED AND ROADWAY DATA

Roadways and vehicle speeds came from the probe vehicle speed data in the NPMRDS. These data were accessed via the Regional Integrated Transportation Information System (RITIS) platform. Speeds are available as a 5-minute harmonic average for each monitored road segment in the traffic message channel (TMC) system. End users can specify the road segments of interest and the time boundaries to receive speed data, and request a download. The data are delivered in a comma-separated value (.csv) file, where one row represents vehicle average speed for a TMC/5-minute interval. The RITIS platform provides a spatial data set of all TMCs for which speed data are collected—a global TMC shapefile—for each U.S. state. These data also contain roadway attributes, such as lane count, annual average daily traffic (AADT), functional class, etc. TMCs are represented as lines.

There is no imputation of speeds within the data set. NPMRDS is built from data sources generated by freight and passenger vehicles. In this analysis, only speeds of passenger vehicles were used. The driving behavior and speed of freight vehicles differs substantially from passenger vehicles due to the extensive driver training completed by freight operators, as well as large differences in the vehicle itself. Future analysis may incorporate freight vehicle speeds, as well as speed differences between freight and passenger traffic, but are outside the scope of this analysis.

The NPMRDS speed data were created using a path-processing algorithm. The path-processing algorithm was meant to limit biases that may result from variable reporting frequencies (e.g., one source may update every second, while others every minute) and slow vehicles providing more data points (e.g., if a vehicle takes longer to traverse a TMC, it will report more frequently). The path-processing algorithm also normalized the data reports across a fixed period. Speeds that were recorded as less than 3 mph or greater than 100 mph were removed from the dataset.

Speeds were validated regularly against data generated by Bluetooth™ and Wi-Fi readers by the University of Maryland's Center for Advanced Transportation Technology (CATT) lab. Validation studies are posted quarterly on different roadway segments to ensure accuracy (Eastern Transportation Coalition 2000). Non-interstate data were checked to be within 10 mph average absolute speed error, and 5 mph of the speed error bias. The average absolute speed error was simply the average of the absolute deviations from the ground truth recorded using Bluetooth™ or Wi-Fi data. The speed error bias was simply the average error (not the absolute value). These validations were typically carried out on the mean speed, as well as relative to the 1.96 standard error around the mean (SEM band).

TMCs were defined as either internal or external. External TMCs are stretches of roadway between major intersections or junctions, while internal TMCs are the short segments that intersect or fly over intersecting roads. Internal TMCs mark a transition point on major roadways and freeways around which large portions of traffic may enter or exit the roadway (see figure 11 for an illustration).

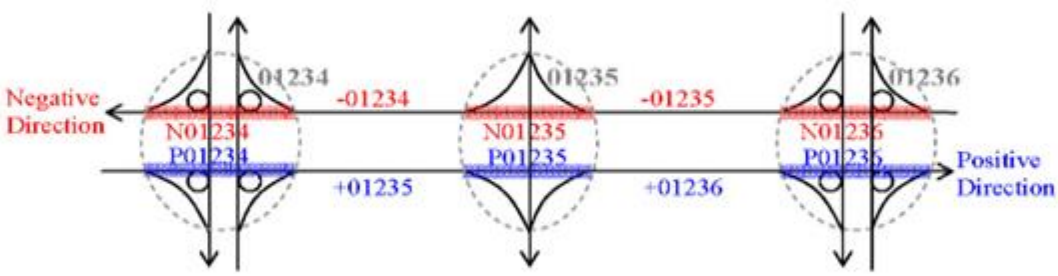

Figure 11. Diagram. Example of internal (red/blue), external (black) TMCs (Source: NPMRDS Analytics).

SPEED LIMIT DATA

Speed limit data were provided by GDOT in the form of a Keyhole Markup Language Zipped (.kmz) file, which is a Google Earth® spatial data format. The data set contains a network of Georgia roadways represented as lines, and each line contains the road segment's speed limit attribute. In this analysis, speed limits were included as ordinal variables for each speed limit in the dataset. Each TMC was assigned a speed limit. This process is described in detail in the "Conflating Speed Limits to TMC" section below.

ECOREGION DATA

Data on ecoregions in the continental United States are publicly available from the Environmental Protection Agency. Land within each ecoregion shares important climatological and ecosystem characteristics (EPA 2018). Many climate and ecosystem characteristics affect driver behavior, as well as the physical geometry of the roadway. For example, fog patterns can vary substantially across Georgia, which affects driving sight distance. Similarly, rainfall can vary a great deal between different regions, which affects braking distance. These factors, thus, influence speed distributions as well as crash frequency. While precise estimates of these factors are difficult to include for every TMC, we assumed that these conditions are similar within each ecoregion, but differ between them. Ecoregions are represented using GIS data, and TMCs were identified as being part of an ecoregion if they fell within the boundaries defined by the EPA.

DATA PREPARATION

Since several sources of data were used to develop models of operating speeds and crashes, a series of steps was used to conflate these data together. Figure 12 is a visual overview of the different sources of data and conflation steps, which are described in detail in Arias 2020.

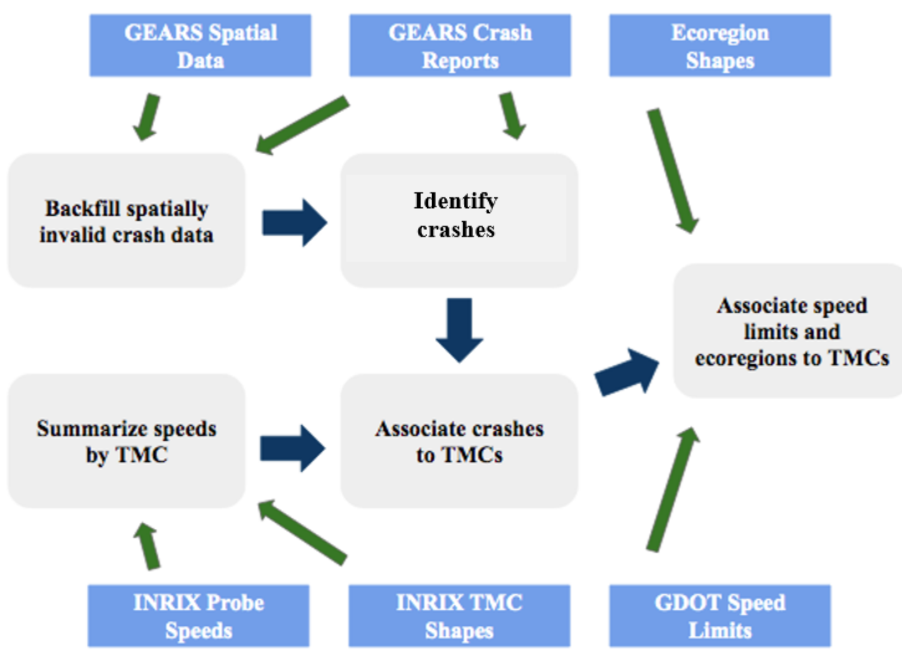

Figure 12. Flowchart. Sequence of steps in data preparation, and their necessary inputs.

Crashes: Validating and Cross-Referencing Invalid Spatial Data with GEARS Reports

The GDOT data set contained 412,035 crashes in 2017. In this data, about 5 percent (24,000) of crashes were outside the boundaries of Georgia or did not correspond to a valid spatial location. In cases where the indicated spatial locations of the crash were invalid, we used the location description of the crash from the GEARS database to identify where the crash occurred.

As a quality assurance measure, we attempted to recover and validate the location of crashes that did not map correctly. All 2017 crash records were pulled from the GEARS online database, which contains latitude and longitude attributes. These records were joined to the invalid spatial crash data by crash ID, a unique identifier in the GEARS crash record. Roughly 11,000 of the 24,000 invalid points were successfully mapped inside the state of Georgia. As a data quality check, 100 of these 11,000 points were randomly selected, and the location described in the crash record itself (e.g. the intersection noted in the crash description) was compared to the mapped location denoted by the latitude and longitude coordinates. For example, if a crash record identified the crash location as 235 Memorial Drive Southeast, the spatial location was checked to determine if the mapped location matched the location identified in the text. All 100 of the points mapped successfully. Overall, the backfilled dataset contained about 399,000 of the initial 421,035 crashes (94.5 percent) in the GDOT crash dataset. These crash data were then mapped onto the TMC network evaluated, resulting in 80,927 crashes analyzed in this research. The process for conflating the number of crashes per TMC is described in detail in Arias, 2020.

TMCs and Speeds

To create a spatial data set of TMC road links containing 2017 speed summaries, speed data were summarized by TMC and combined with the spatial data. Figure 13 shows the included TMCs and their relative 85th percentile speeds. TMCs were considered for inclusion if probe vehicle speeds were collected in 2017 and had more than 1,000 speed observations in a given year.

In this analysis, 7,050 TMCs were included, with nearly 93 percent of TMCs located on arterial roadways (table 4).

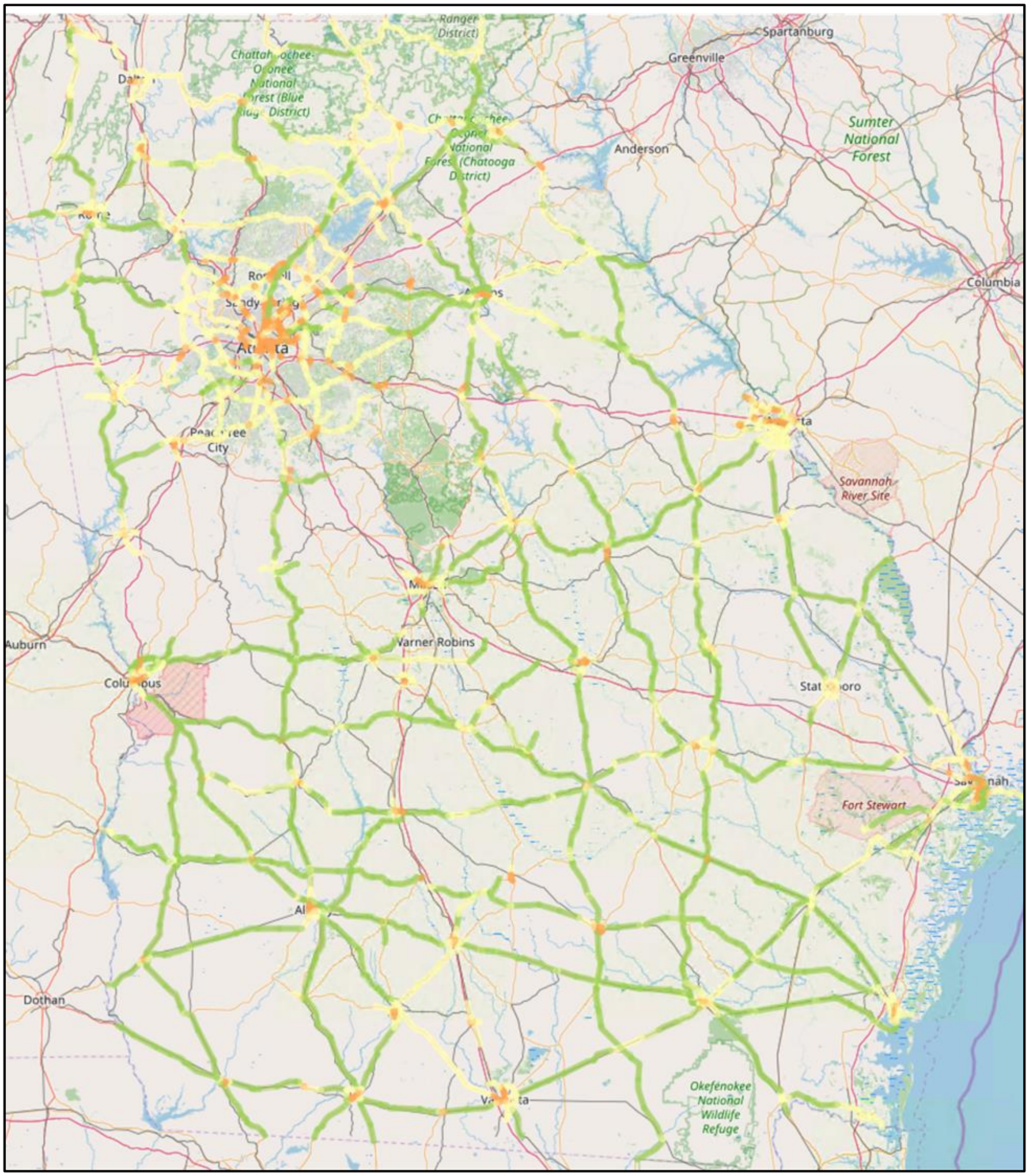

Figure 13. Map. Arterial roadways highlighted by 85th percentile speed on each TMC (figure from Arias, 2020).

Table 4. Included TMCs by functional class.

Functional Class	Count
Major Arterial	6,318
Minor Arterial	640
Major Collector	74
Minor Collector	0
Local	18
Total	**7,050**

Data Conflation Results

As noted previously, the different data sources in this analysis required a conflation process so they could be evaluated on the same scale. Figure 12 above shows a flowchart of steps in data preparation and the inputs needed to complete those steps. All data preparation was completed in R® statistical software and/or ArcMap™ for spatial data.

Road characteristics vary widely among TMCs. TMC length varies by several orders of magnitude, from a few thousandths of a mile to over 12 miles. AADT ranges from under 1,000 vehicles daily to over 100,000, and speed percentiles range by 60–70 mph. A broad variety of road types and contexts are present in the data set. For the single corridor analysis on Georgia State Route 6, the summary statistics are presented in table 8. Less variation exists in this subset of TMCs. Additional supplementary analyses were completed for only TMCs longer than 0.025 mile, those with more than 13,000 AADT, those with less than 13,000 AADT, and during time periods corresponding to peak and off-peak commuting hours. For the analysis limited to specific times of day, only TMCs with 1,000 speed observations during the specified time were maintained in the analysis.

Table 5. Summary statistics for each TMC on State Route 6.

	Median	Min	Max	Std. Deviation
TMC Length (miles)	0.579	0.006	7.6	1.32
Crashes	5	0	60	13
AADT (veh/day)	29,900	1,420	71,600	16,874
Speed Limit (mph)	55	35	65	–
Speed (mph)				
15th Percentile	29	7	62	13.8
Median	43	17	67	11.9
85th Percentile	53	34	72	9.38
Low Speed Diff. (Median−15th)	11	5	–	4.01
High Speed Diff. (85th−Median)	9	4	23	3.27

Table 6. Summary statistics for each TMC.

	Mean	Median	Min	Max	Std. Deviation
TMC Length (miles)	1.556	0.711	0.004	12.23	2.13
Crashes	11.48	4	0	289	18.9
Injuries	4.49	1.00	0	76	7.37
Fatalities	0.046	45	0	9	0.281
Speed (mph)					
Posted Speed Limit	48.00	45	20	70	9.38
85th Percentile	48.81	48	17	87	12.01
Median	40.13	39	9	68	14.10
15th Percentile	29.99	27	4	64	15.54
High Speed Diff. (85th−Median)	8.68	8	2	45	3.35
Low Speed Diff. (Median−15th)	10.13	10	2	36	3.77
AADT (veh/day)	17,800	14,641	531	119,000	13,604
Number of Through Lanes	3.59	4	1	8	1.13

METHODS FOR STATISTICAL MODELING

Negative binomial regressions were used to assess the relationship between relevant roadway features, speed, and crash counts. Negative binomial models are appropriate for modeling crash counts, as crash counts are a nonzero distribution where rates over space or time are quantified. Conventional ordinary least squares regression models are inappropriate for modeling the number of crashes where outcomes are strictly zero or above. Thus, count models were tested and used in this analysis. Typically, Poisson and NB (also known as the Poisson–gamma) models are used to model crash risk. Both were tested in an initial case study on Georgia Route 6 and then applied to the full arterial network. Unlike Poisson models, the negative binomial accounts for when the variance is larger than the mean, a phenomenon known as overdispersion. The variance of crashes at a particular TNC in this analysis substantially exceeds the mean number of crashes, violating a key assumption of the Poisson distribution. NB regression has been used in numerous studies of crash counts (Lord and Mannering 2010).

NB models are a generalization of Poisson that differs by adding a parameter to account for overdispersion. The NB mean value is Poisson distributed. In this analysis we assumed that the number of crashes at the *i*th TMC having a mean value of y_i crashes per year is given by the equation in figure 16.

$$P(y_i) = \frac{EXP(-\lambda_i)\lambda_i^{y_i}}{y_i!}$$

Figure 14. Functional form for the negative binomial model.

The Poisson parameter, lambda, is given by the following, $\lambda_i = EXP(\beta X_i + \varepsilon_i)$. The error term, $EXP(\varepsilon_i)$, differentiates the negative binomial from the Poisson distribution, as it is gamma distributed with mean 1 and variance equal to α (the overdispersion parameter). This allows the mean to differ from the variance. β is a vector of unknown coefficients that are estimated from the model, while X_i is a vector of the explanatory variables observed at the TMC level, which include annual percentile speeds, differences in annual percentile speeds, the posted speed limit (factor with levels for each speed limit on the corridor), number of lanes (factor), categories for different levels of AADT, and the length of the TMC in miles, as well as metrics for short TMCs.

CHAPTER 5 RESULTS

In the following sections, we present the results of the analyses of percentile speed data and annual crashes. As noted above, the results are presented for a single corridor (Georgia Route 6), and the network of arterial roadways in Georgia. For both analyses, the results for percentile speeds, then differences in percentile speeds are presented.

GEORGIA STATE ROUTE 6 ANALYSIS

In this section we present two sets of models—those with individual percentile speeds as independent variables, and those with differences in percentile speeds as independent variables.

Percentile Speed Models

The coefficients on the annual 15th percentile speed were consistently negative and small in magnitude, suggesting that as the 15th percentile speed increases, the number of annual crashes on a specific TMC would decrease slightly, on average. This result was consistent across all models, regardless of other variables included in the model. Similarly, the coefficient on the median speed was negative in all but the one model that also included 15th percentile speed (table 9, column 4). Again, this suggests increases in median speed would be associated with decreases in crashes.

Table 7. Negative binomial model of percentile speeds on total annual crashes per TMC on Georgia State Route 6.

	(1) Total Crashes	(2) Total Crashes	(3) Total Crashes	(4) Total Crashes	(5) Total Crashes	(6) Total Crashes	(7) Total Crashes	(8) Total Crashes
Intercept	-7.07	-11.3***	-8.30***	-8.99***	-10.2***	-11.5***	-7.77***	-8.36***
15th Percentile Speed	-0.032	-0.020	-0.043***	-0.058*	-0.063***	–	–	–
Median Speed	-0.084	-0.119^{+}	–	0.019	–	-0.159***	-0.041***	–
85th Percentile Speed	0.085	0.129*	–	–	0.033	0.154***	–	-0.039**
Ln(AADT)	0.848***	1.16***	1.10***	1.13***	1.17***	1.158***	1.10***	1.19***
Lanes	0.160	–	–	–	–	–	–	–
TMC Length (miles)	0.535***	0.480***	0.486***	0.498***	0.504***	0.461***	0.427***	0.389***
Observations	149	149	149	149	149	149	149	149
2*(*LL*)	-852.9	-878.1	-884.0	-883.4	-881.5	-878.6	-890.8	-899.0

$^{+}p < 0.10$ $*p < 0.05$ $** p < 0.01$ $*** p < 0.001$

Coefficients on the 85th percentile speeds yielded results that were inconsistent and varied depending on which other percentile speed covariates were included. For example, in models with only the 85th percentile and median speeds, respectively, the percentile speed coefficients were negative and similar in magnitude (table 9, columns 7 and 8), suggesting a small decrease in expected crashes when either percentile speed increased. However, the coefficients on the 85th percentile speed and median speed were similar magnitude but opposite in direction (table 9, column 6) when both were included in the model. This suggests that including only one percentile speed in a model of crash counts may not capture the full effect of speed changes. Further, percentile speeds were highly correlated with each other. A change in an individual percentile speed is, thus, difficult to interpret. Therefore, we included differences in percentile speeds to better assess whether changes in the speed distribution influenced the expected number of crashes. These results are discussed in the next section, "Differences in Percentile Speed Models."

Control variables for traffic volume, i.e., ln(AADT), and segment length in miles were significant and positively correlated with increased crashes. This correlation is to be expected, and both variables increase exposure for any particular vehicle.

Differences in Percentile Speed Models

Based on the important interactions between the percentile speeds, additional models were run using differences in percentile speeds instead. *Differences* in percentiles speeds were significant, positive, and larger in magnitude than individual percentile speeds. When modeled separately, both the *85th percentile−median* difference and *median−15th percentile* difference are significant and positive, albeit with different magnitudes. Models assessing the lower portion of the speed distribution (difference between median and 15th percentile speed) alone suggest a small change in the expected number of crashes, as the median is larger relative to the 15th percentile (table 10, column 4). Models only considering the higher portion of the distribution (difference between 85th percentile and median speeds) suggest a stronger relationship with the expected number of crashes (table 10, column 3).

Table 8. Negative binomial model of speed differences on total annual crashes per TMC.

	(1) Total Crashes	(2) Total Crashes	(3) Total Crashes	(4) Total Crashes
Intercept	-11.5***	-12.3***	-12.07***	-14.5***
85^{th} Percentile Speed−Median	0.164**	0.158***	0.166**	
Median−15^{th} Percentile Speed	0.011	0.0125		0.069**
Ln(AADT)	1.11***	1.20***	1.18***	1.52***
4 Total Lanes	0.051			
6 Total Lanes	-0.034			
TMC Length (miles)	0.483***	0.470***	0.459***	0.412***
Observations	149	149	149	149
2*(*LL*)	-854.7	-878.6	-878.81	-900.2

$^{+}p < 0.10$ $^{*}p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

When both differences are included in the same model, the higher speed difference is significant and larger in magnitude than the lower speed difference (table 10, column 2). The coefficient on low-speed difference is not significantly different from zero in this model, suggesting that the high-speed difference might be a better means of predicting the expected crash counts per TMC. In all models examining the relationship between speed differences and expected crashes per TMC, the control variables for traffic volume and segment length were positive and significant, as expected. The total number of lanes, and speed limits were not significant in any models in this analysis. The speed limit control variables were close to zero. In this case study, there was no variation in functional class, and relatively little variation in posted speed limit and number of lanes. It is possible that with a larger sample of roadways, there would be more variation in crashes and speeds across different geometries and posted speed limits, and a quantifiable relationship would be detected.

As the difference between 85th percentile and median speed increases, the expected number of crashes increases at a higher rate when AADT is higher (based on model results in table 10, column 3). For example, as the difference between 85th percentile and median speed increases from 5 to 10 on a TMC with 30,000 vehicles, the expected number of crashes increases from approximately four crashes to nine crashes per year.

FULL GEORGIA DEPARTMENT OF TRANSPORTATION ARTERIAL NETWORK

The GDOT arterial network in this analysis consists of 10,971 lane miles of roadways, 7,272 signalized intersections, and 7,050 TMCs. All seven GDOT districts are represented in this analysis, which includes large metropolitan areas, small cities and towns, and sparsely populated rural areas. Posted speed limits range from 25 mph to 70 mph, and AADT ranges from 530 to 119,000 vehicles per day. In 2017, 80,927 crashes were identified on this roadway network.

In each of the models, we include the same set of covariates: ordinal variables for AADT, a variable controlling for especially short TMCs (i.e., 0.025 mile or shorter), the length of each

TMC in miles, a categorical variable corresponding to the ecoregion where the TMC is located, and a categorial variable for whether the TMC is located in an urban, small urban, or rural area. Numerous models were fit to determine the proper means of assessing covariates. Model results with additional covariates and specifications are available in Appendix A.

Percentile Speed Models

In all models, speed percentiles and differences were significantly related to the expected number of crashes per TMC. However, specific percentile speeds did not influence the predicted number of crash outcomes in the same way as differences between percentile speeds.

Models were run using 5th percentile speed, 15th percentile speed, median speed, 85th percentile speed, and 95th percentile speed with the same set of covariates. The relationship between crashes and speed percentiles was initially modeled with each of the percentile speeds listed above as the only metric of speed. In all models (Table 11, columns 1–5), the coefficient was negative, significant, and ranged from 0.044 to 0.046. After modeling the individual percentile speeds, different combinations of percentile speeds were tested. Unlike models using only one percentile speed, combinations of percentile speeds yielded results that were inconsistent. The respective signs and magnitudes of coefficients changes depending on the combinations of percentile speeds included in the model.

Coefficients on the 85th percentile speeds yielded results that were inconsistent and varied depending on which other percentile speed covariates were included. For example, in models with only the 85th percentile and median speeds, respectively, the percentile speed coefficients were negative and similar in magnitude (Table 11, columns 7 and 8), suggesting a small decrease in expected crashes when either percentile speed increased. However, the coefficients on the 85th percentile speed and median speed were similar magnitude but opposite in direction (Table 11, column 6) when both were included in the model. In further models with varying combinations of percentile speeds as explanatory variables, the coefficients on median and 85th percentile speed were significant in combination with one another and alone. The 85th percentile and median speed were not statistically significant ($p < 0.10$) when modeled pairwise with 15th percentile speed (Table 11, column 6). This suggests that including only one percentile speed in a model of crash counts may not capture the full effect of speed changes. We, thus, included differences in percentile speed values to better assess whether changes in the speed distribution influenced the expected number of crashes. These results are discussed in the next section, “Differences in Percentile Speed Models.”

Table 9. Negative binomial model of percentile speeds on total annual crashes per TMC.

	Dependent Variable							
	Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	2.469***	2.817***	3.470***	4.040***	4.150***	3.074***	2.956***	2.874***
Percentile Speeds								
5th	-0.045***						-0.028***	-0.068***
15th		-0.044***				-0.031***		0.074***
50th			-0.045***			-0.014	-0.021***	-0.077***
85th				-0.046***		-0.001		0.021
95th					-0.043***		0.0001	0.001
Traffic Volume								
30–49,999 AADT	0.548***	0.540***	0.559***	0.602***	0.613***	0.547***	0.551***	0.552***
≥ 50,000 AADT	0.692***	0.635***	0.596***	0.658***	0.737***	0.620***	0.641***	0.632***
TMC Length								
Short TMC	-1.095***	-1.093***	-0.996***	-0.930***	-0.904***	-1.063***	-1.062***	-1.021***
Total TMC Length (miles)	0.348***	0.360***	0.354***	0.334***	0.317***	0.361***	0.359***	0.351***
Land Use Context								
Urban TMC	0.537***	0.505***	0.471***	0.475***	0.510***	0.490***	0.499***	0.499***
Rural TMC	-0.671***	-0.710***	-0.790***	-0.879***	-0.936***	-0.724***	-0.683***	-0.671***
Ecoregion								
Piedmont	0.117	0.077	-0.021	-0.105	-0.131	0.050	0.077	0.071
Ridge and Valley	-0.115	-0.162	-0.287**	-0.393***	-0.448***	-0.193	-0.156	-0.165
Southeastern Plain	-0.417***	-0.483***	-0.630***	-0.736***	-0.768***	-0.524***	-0.483***	-0.491***
Southern Coastal Plain	-0.353***	-0.403***	-0.527***	-0.633***	-0.668***	-0.439***	-0.409***	-0.415***
Observations	7,050	7,050	7,050	7,050	7,050	7,050	7,050	7,050
Log Likelihood	-21,342	-21,346	-21,369	-21,441	-21,504	-21,339	-21,311	-21,290

$^{+}p < 0.10$ $^{*}p < 0.05$ $^{**}p < 0.01$ $^{***}p < 0.001$

Differences in Percentile Speed Models

Results using percentile speeds suggested that interactions among recorded percentile speeds are important. Frequently, percentile speed coefficients were close to equal in magnitude and opposite in direction. Further, signs and magnitudes of coefficients would change depending on the different covariates that were included in the model. It is unlikely that only one speed percentile would change at a time; thus, it is critical to model overall changes in the distributions of speed. Modeling differences between percentile speeds can help account for changes in speed distributions.

Based on the important interactions between the percentile speeds, additional models were run using differences in percentile speeds instead. *Differences* in percentiles speeds were significant, positive, and larger in magnitude than individual percentile speeds. When modeled separately, both the *85th percentile−median* difference and *median−15th percentile* difference are significant and positive, albeit with different magnitudes. The 0.02 coefficient on the lower portion of the speed distribution (difference between median and 15th percentile speed) modeled alone suggests a relatively weak, but statistically relationship between the expected number of crashes and an increasing difference between the median and 15th percentile speed (table 12, column 1). Conversely, models only considering the upper end of the speed distribution (either the difference between 85th percentile and median speeds, or the difference between the 95th and 85th percentile speeds) or the overall speed dispersion (95th−5th percentile) suggest a stronger relationship with the expected number of crashes (table 12, columns 2–4).

When the low-speed difference is included in the same model as estimates of differences in the upper end or the entire speed distribution (table 12, columns 5–8), the metrics accounting for very high speeds are significant and larger in magnitude than the lower speed difference. This result suggests that the high-speed difference might be a better means of predicting the expected crash counts per TMC. In all models examining the relationship between speed differences and expected crashes per TMC, the control variables for traffic volume and segment length were positive and significant, as expected. The binary variable for a TMC less than 0.025 mile is negative in all analyses. This is likely related to the fact that longer TMCs have more space, providing more opportunities for crashes. Urban TMCs were expected to have the highest number of crashes, followed by small urban TMCs, and rural TMCs; this was consistent in all models. Ecoregion variables were also significant. All other things being equal, TMCs in the Ridge and Valley, Southeastern Plain, and Southern Coastal Plain were expected to have fewer annual crashes than TMCs in the Piedmont and Blue Ridge regions. Results related to each of these variables are discussed in detail below. When injuries were used as the outcome variable, the coefficients on all variables were slightly smaller in magnitude, but in the same direction as those for models with crashes as the outcome variable (Appendix A Table 19, and Table 20). This result is not surprising as the number of crashes and injuries per TMC is highly correlated (Appendix A Table 33). The total number of lanes and speed limits were not significant in any models in this analysis; those results are available in Appendix A.

Table 10. Negative binomial model of speed differences on total annual crashes per TMC.

	Dependent Variable							
	Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.89***	1.04***	0.99***	1.47***	1.13***	1.02***	1.05***	1.25***
Speed Difference Metrics								
Low Speed Difference (Median−15th)	0.02***				-0.02***	-0.01*	-0.01**	0.02***
High Speed Difference (85th−Median)		0.10***			0.11***	0.05***	0.09***	
Speed Dispersion (95th−5th)			0.08***			0.05***		
Excessive Speed Difference (95th−85th)				0.13***			0.04***	0.13***
Traffic Volume								
30–49,999 AADT	0.55***	0.47***	0.46***	0.50***	0.46***	0.46***	0.46***	0.49***
≥ 50,000 AADT	0.77***	0.61***	0.54***	0.58***	0.58***	0.54***	0.55***	0.60***
TMC Length								
Short TMC	-1.01***	-1.10***	-1.06***	-0.98***	-1.07***	-1.07***	-1.07***	-1.02***
Total TMC Length (miles)	0.24***	0.28***	0.28***	0.27***	0.28***	0.29***	0.29***	0.27***
Land Use Context								
Urban TMC	0.64***	0.61***	0.58***	0.58***	0.59***	0.58***	0.59***	0.60***
Rural TMC	-1.24***	-1.08***	-1.08***	-1.17***	-1.09***	-1.08***	-1.08***	-1.14***
Ecoregion								
Piedmont	-0.17	-0.05	-0.07	-0.16	-0.07	-0.07	-0.07	-0.12
Ridge and Valley	-0.57***	-0.42***	-0.44***	-0.53***	-0.45***	-0.44***	-0.44***	-0.48***
Southeastern Plain	-0.80***	-0.65***	-0.68***	-0.79***	-0.68***	-0.68***	-0.68***	-0.73***
Southern Coastal Plain	-0.67***	-0.50***	-0.53***	-0.65***	-0.53***	-0.53***	-0.53***	-0.60***
Observations	7,050	7,050	7,050	7,050	7,050	7,050	7,050	7,050
Log Likelihood	-21,837	-21,710	-21,695	-21,762	-21,703	-21,691	-21,695	-21,753

$^{+}p < 0.10$ $^{*}p < 0.05$ $^{**}p < 0.01$ $^{***}p < 0.001$

As the binomial coefficients are difficult to interpret, figure 17 displays the marginal effect of increasing difference between 85th percentile and median speed on expected number of crashes is displayed at varying levels of AADT (based on model results in table 12, column 3). As expected, trend lines for different volumes of traffic differ. More crashes are expected when there are higher AADT. As the difference between 85th percentile and median speed increases from 5 to 10 on a TMC with 30,000 vehicles, the expected number of crashes increase from approximately 40 crashes to 90 crashes per year.

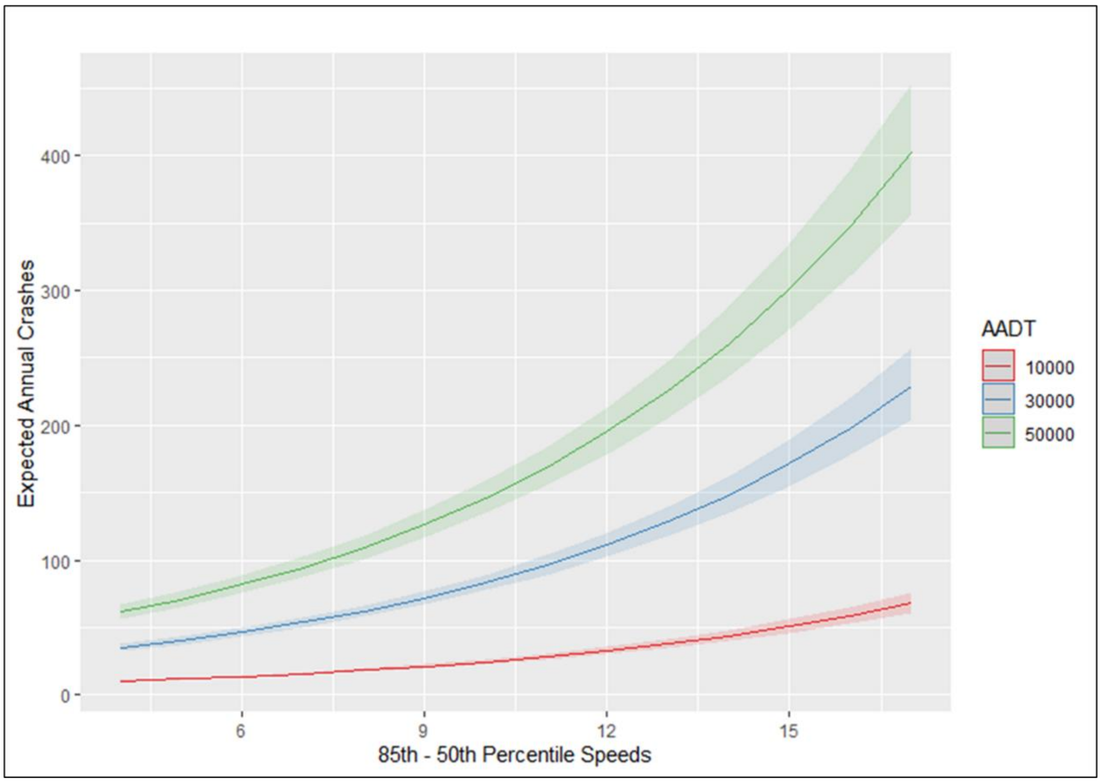

Figure 15. Modeled expected annual crashes according to difference between 85th percentile and 50th percentile speeds by AADT category.

Urban/Small Urban/Rural

The land use designation was an important factor in this analysis. About 80 percent of crashes occur on urban TMCs, which account for 52 percent of TMCs in this analysis (table 13).

Similarly, urban TMCs account for most injuries on the TMC network. Conversely, rural TMCs account for the majority of TMC miles in this analysis (56.8 percent), despite only accounting for 28.2 percent of TMCs. Despite accounting for many of the TMC miles in this analysis, relatively few crashes happen on rural TMCs (8.7 percent). However, when crashes occur on rural TMCs, they tend to be severe. Rural TMCs accounted for about 37 percent and 38 percent of serious injuries and deaths, respectively.

Table 11. Crashes and TMC characteristics in urban, small urban, and rural areas.

	Total	Urban	Small Urban	Rural
Crash Outcomes				
Crashes	80,927	64,786	9,044	7,097
Injuries	30,949	23,746	3,658	3,545
Serious Injuries	3,006	1,291	603	1,112
Deaths	325	155	46	124
TMC Characteristics				
Miles	10,971	3,085	1,650	6,236
TMCs	7,050	3,711	1,350	1,989

In all models (Table 12), the location of a TMC in an urban, small urban, or rural area was significantly related to an expected increase in crashes. Urban areas had the highest number of expected crashes, followed by small urban TMCs, and rural TMCs. Urban areas have the highest population, and tend to have the most traffic. However, operating speeds and crash risks tend to differ across land use context.

The 85th percentile speed differs between urban, small urban, and rural areas. In figure 18, the distribution of 85th percentile speeds are displayed. Eighty-fifth percentile speeds on TMCs in urban areas tend to be lower than those in small urban and rural areas. The average 85th percentile speed, demarcated by the hashed red line, on an urban TMC is 43.3 mph. Most 85th percentile speeds fall in the 30–60 mph range on urban TMCs. On rural TMCs, the average 85th percentile speed is 59.4 mph, demarcated by the hashed blue line. The recorded 85th percentile speeds on rural TMCs are left skewed with a far higher proportion of speeds above 60 mph than urban and small urban TMCs. Thus, the highest speeds on rural TMCs tend to be higher than those on small urban and urban TMCs. Small urban TMCs are sometimes similar to urban TMCs, while other times resembling rural TMCs, which influences speeds. This is displayed in figure 18 where the distribution of 85th percentile speeds is bimodal, with peaks around 40 and 60 mph.

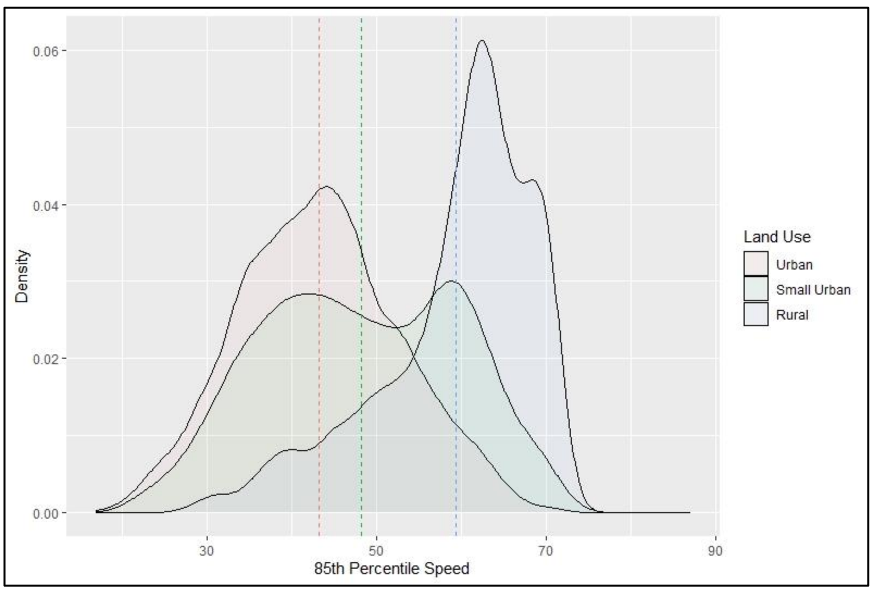

Figure 16. Line graph. 85th percentile speeds by land use type.

In addition to the relatively high 85th percentile speeds on rural roads, the overall distribution of speeds on rural TMCs tends to be smaller in magnitude. In figure 19, the distribution of speed dispersions (defined as the *95th−5th percentile speed*) is displayed by land use type. The speed dispersion on rural TMCs tends to be relatively small. Thus, the speeds on rural TMCs tend to vary less over the course of the day and year. Operating speeds on rural TMCs, thus, tend to be relatively close over the course of the year. Conversely, the speed dispersions on urban and small urban TMCs tend to be larger, likely reflecting the range of traffic conditions on urban and small urban TMCs. Urban and small urban TMCs tend to have higher traffic volumes and more congestion.

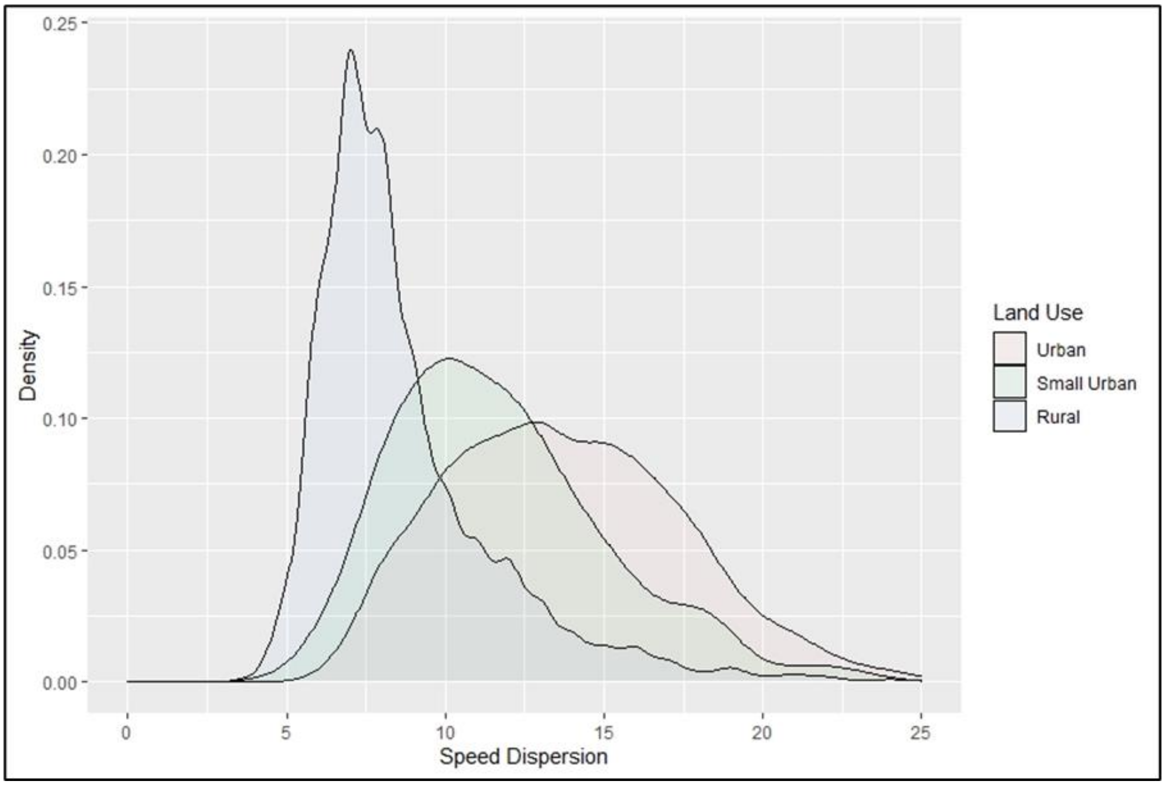

Figure 17. Line graph. Speed dispersion (95th−5th percentile speeds) on TMCs by land use type.

Ecoregions

Ecoregions were significant in all models run and are included below. Ecoregions experience different sunlight and weather patterns, and topography varies between each. Thus, different ecoregions are likely to have diverse operating speeds and risks of crashes. In this analysis, the Blue Ridge region is the reference category. TMCs in the Piedmont region, the largest and most populated ecoregion in Georgia, had a positive coefficient and are expected to have a higher crash frequency than TMCs in the Blue Ridge region, all things being equal. However, none of the coefficients were significantly different than the Blue Ridge region. TMCs in Ridge and Valley, Southeastern Plain, and Southern Coastal Plain regions all had negative coefficients and were expected to have fewer annual crashes than TMCs in the Blue Ridge region, all things being equal. The magnitude and significance varied for these ecoregions depending on the covariates included. However, the coefficients on these ecoregions were consistently negative and similar in magnitude in all models.

TMC Length

To check for the robustness of results, models were run only on those TMCs that were 0.025 mile or longer. This cutoff was used in Erhardt et al. 2019 to eliminate TMCs that are not representative of roadway segments in the larger network.

There are 781 TMCs that are 0.025 mile or shorter. About 68 percent or 529 are classified as urban, 18 percent or 140 as small urban, and the remaining 14 percent or 112 were classified as rural TMCs.

After running models on only those TMCs longer than 0.025 mile, the estimated coefficients changed very little. Like the full network, the coefficient on the low-speed difference ranges from −0.02 to 0.02 and changes depending on which other speed difference metrics are included. Similarly, coefficients on the high-speed difference, speed dispersion, and excessive speed difference were significant, positive, and much larger in magnitude than the low-speed difference. The coefficients on these metrics varied from 0.07 to 0.15, with the exception of one model where the high-speed difference was not significantly different from zero (table 14, column 6). In models of the full network, these coefficients ranged from 0.05 to 0.13

(Table 12). The control variables for AADT, overall TMC length, land use context, and ecoregion were all similar to prior models.

Table 12. Difference in percentile speed models, limited to TMCs longer than 0.025 mile.

	Dependent Variable = Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.96***	1.11***	0.99***	1.38***	1.22***	1.06***	1.08***	1.22***
Speed Difference Metrics								
Low Speed Difference (Median−15th)	0.02***				-0.02***	-0.01*	-0.01**	0.01**
High Speed Difference (85th−Median)		0.09***			0.11***	0.02	0.08***	
Speed Dispersion (95th–5th)			0.08***			0.07***		
Excessive Speed Differences (95th–85th)				0.15***			0.07***	0.15***
Traffic Volume								
30–49,999 AADT	0.56***	0.47***	0.46***	0.49***	0.46***	0.45***	0.45***	0.48***
≥ 50,000 AADT	0.75***	0.57***	0.50***	0.53***	0.53***	0.48***	0.49***	0.54***
TMC Length								
Short TMC								
Total TMC Length (miles)	0.24***	0.28***	0.29***	0.27***	0.29***	0.29***	0.29***	0.27***
Land Use Context								
Urban TMC	0.63***	0.60***	0.58***	0.57***	0.59***	0.57***	0.58***	0.58***
Rural TMC	-1.28***	-1.12***	-1.11***	-1.19***	-1.12***	-1.11***	-1.11***	-1.17***
Ecoregion								
Piedmont	-0.19	-0.07	-0.08	-0.16	-0.10	-0.10	-0.10	-0.13
Ridge and Valley	-0.58***	-0.45***	-0.45***	-0.53***	-0.48***	-0.46***	-0.46***	-0.49***
Southeastern Plain	-0.82***	-0.68***	-0.69***	-0.79***	-0.71***	-0.71***	-0.71***	-0.75***
Southern Coastal Plain	-0.66***	-0.50***	-0.52***	-0.62***	-0.53***	-0.53***	-0.53***	-0.59***
Observations	6,269	6,269	6,269	6,269	6,269	6,269	6,269	6,269
Log Likelihood	-20,037	-19,935	-19,910	-19,952	-19,926	-19,908	-19,913	-19,948

$^{+}p < 0.10$ *$p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

AADT Categories

To ensure that the estimated relationships were not influenced by the accuracy of the observed speed data reported at the TMC level, the same models were run on only those TMCs where 13,000 or more AADT per day are reported. This eliminated 3,193 TMCs from the analysis, leaving about 55 percent of the initial 7,050. Once again, the estimated coefficients on speed differences changed very little, if at all. The low-speed difference coefficients ranged from −0.03 to 0.003, while the other speed difference coefficients ranged from 0.05 to 0.13 (table 15). This is similar to the results using the full network, as well as TMCs larger than 0.025 mile (table 14). One notable difference when removing TMCs with relatively low traffic was that most ecoregion coefficients were no longer significant. We also ran this model on only those TMCs with less than 13,000 AADT. Once again, the low-speed difference was small in magnitude relative to metrics that include higher speeds, and the higher speed differences were consistently positive and ranged from 0.05 to 0.11 (table 16). Several ecoregions dropped out of this analysis as there were not enough observations within them.

Table 13. Differences in percentile speed models, statewide crashes TMCs with 13,000 or more AADT.

	Dependent Variable= Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.78***	0.61***	0.54***	1.04***	0.85***	0.72***	0.73***	0.99***
Speed Difference Metrics								
Low Speed Difference (Median−15th)	-0.001				-0.03***	-0.02***	-0.02***	0.003
High Speed Difference (85th−Median)		0.09***			0.11***	0.03*	0.08***	
Speed Dispersion (95th−5th)			0.07***			0.06***		
Excessive Speed Differences (95th−85th)				0.13***			0.05***	0.13***
Traffic Volume								
30–49,999 AADT	0.50***	0.43***	0.42***	0.45***	0.43***	0.42***	0.42***	0.45***
≥ 50,000 AADT	0.75***	0.64***	0.58***	0.60***	0.59***	0.56***	0.57***	0.60***
TMC Length								
Short TMC	-0.81***	-0.89***	-0.87***	-0.82***	-0.85***	-0.85***	-0.85***	-0.82***
Total TMC Length (miles)	0.40***	0.48***	0.48***	0.44***	0.48***	0.48***	0.48***	0.44***
Land Use Context								
Urban TMC	0.44***	0.43***	0.40***	0.39***	0.40***	0.39***	0.39***	0.39***
Rural TMC	-0.97***	-0.83***	-0.82***	-0.89***	-0.83***	-0.83***	-0.83***	-0.88***
Ecoregion								
Piedmont	0.26	0.44**	0.41**	0.32*	0.40**	0.39**	0.39**	0.32*
Ridge and Valley	-0.14	0.06	0.06	-0.03	0.01	0.02	0.02	-0.03
Southeastern Plain	-0.05	0.19	0.17	0.05	0.13	0.13	0.13	0.06
Southern Coastal Plain	-0.03	0.22	0.18	0.05	0.16	0.15	0.15	0.06
Observations	3,857	3,857	3,857	3,857	3,857	3,857	3,857	3,857
Log Likelihood	-14,200	-14,126	-14,105	-14,135	-14,111	-14,099	-14,102	-14,135

$^{+}p < 0.10$ $^{*}p < 0.05$ $^{**}p < 0.01$ $^{***}p < 0.001$

Table 14. Differences in percentile speed models, statewide crashes TMCs with less than 13,000 AADT.

	Dependent Variable = Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.44^{***}	0.94^{***}	0.95^{***}	1.45^{***}	0.91^{***}	0.87^{***}	0.88^{***}	1.09^{***}
Speed Differences								
Low Speed Difference (Median−15th)	0.04^{***}				0.01	0.01	0.01	0.04^{***}
High Speed Difference (85th−Median)		0.10^{***}			0.09^{***}	0.06^{***}	0.09^{***}	
Speed Dispersion (95th−5th)			0.07^{***}			0.02^{*}		
Excessive Speed Differences (95th−85th)				0.11^{***}			0.02	0.08^{***}
Traffic Volume								
30–49,999 AADT	-1.02^{***}	-1.06^{***}	-1.00^{***}	-0.91^{***}	-1.07^{***}	-1.06^{***}	-1.06^{***}	-1.00^{***}
≥ 50,000 AADT	0.21^{***}	0.23^{***}	0.24^{***}	0.23^{***}	0.23^{***}	0.23^{***}	0.23^{***}	0.22^{***}
TMC Length								
Short TMC	0.23^{***}	0.25^{***}	0.23^{***}	0.20^{**}	0.25^{***}	0.25^{***}	0.25^{***}	0.22^{***}
Total TMC Length (miles)	-0.99^{***}	-0.88^{***}	-0.89^{***}	-1.00^{***}	-0.87^{***}	-0.87^{***}	-0.87^{***}	-0.93^{***}
Land Use Context								
Urban TMC	-0.16	-0.10	-0.13	-0.20	-0.10	-0.10	-0.10	-0.13
Rural TMC	-0.66^{***}	-0.54^{***}	-0.57^{***}	-0.67^{***}	-0.54^{***}	-0.54^{***}	-0.54^{***}	-0.60^{***}
Ecoregion								
Piedmont	-0.80^{***}	-0.77^{***}	-0.80^{***}	-0.89^{***}	-0.76^{***}	-0.76^{***}	-0.76^{***}	-0.78^{***}
Ridge and Valley	-0.93^{***}	-0.86^{***}	-0.88^{***}	-0.96^{***}	-0.86^{***}	-0.85^{***}	-0.86^{***}	-0.89^{***}
Observations	3,193	3,193	3,193	3,193	3,193	3,193	3,193	3,193
Log Likelihood	-7,291	-7,251	-7,258	-7,295	-7,250	-7,249	-7,250	-7,274

$^{+}p < 0.10$ $^{*}p < 0.05$ $^{**}p < 0.01$ $^{***}p < 0.001$

Time of Day Segmentation

Traffic volume changes substantially over the course of a day. Generally, most traffic occurs during peak commuting hours. The volume at any given time of time also influences the overall operating speed on a roadway and the crash risk. Speeds and speed distributions are very likely to differ depending on the hour of day. For example, slower speeds are likely during peak commuting hours in congested areas. Outside peak commuting hours, congestion may decrease and speeds may increase. Therefore, we analyzed speeds within specific time periods to determine the modeled relationships between operating speeds and crashes on TMCs changes. In this analysis, we analyzed speeds and crashes occurring during the following time periods: AM Peak (6:00–9:59), Midday (10:00–15:59), PM Peak (16:00–19:59), Evening (20:00–23:59), and Overnight (24:00–5:59).

Figure 20 displays the distribution of 85th percentile speeds. Across all time periods, the 85th percentile speeds are bimodally distributed across TMCs with peaks around 40 mph and 60 mph. During the evening and overnight time periods, 85th percentile speeds tend to be higher than the morning peak, evening peak, and midday periods. Traffic and congestion are higher in the daytime hours, and the relative lack of vehicles on the roadway allows for individuals to drive at higher speeds should they choose to do so.

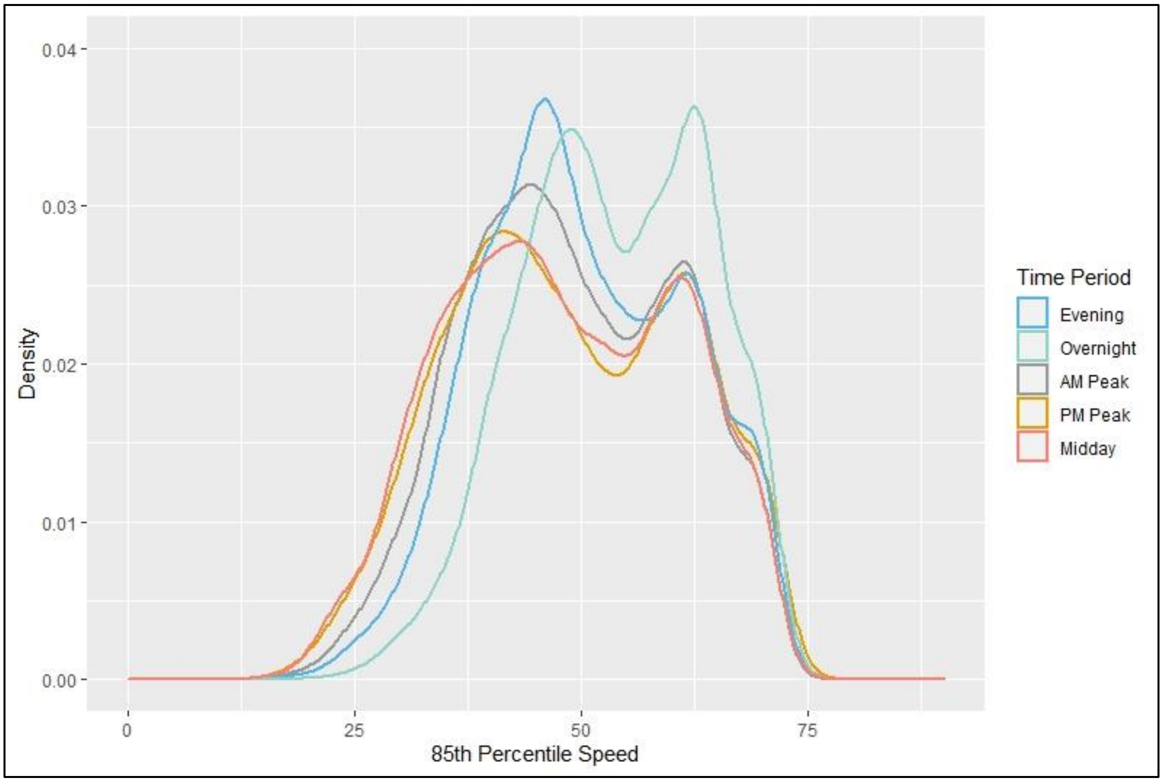

Figure 18. Line graph. Distribution of 85th percentile speeds by time of day.

Similarly, 15th percentile speeds also tend to be higher during the evening and overnight periods relative to daytime speeds (figure 21). Unlike 85th percentile speeds, the 15th percentile speeds tend to vary more within any category. The 15th percentile speeds during the overnight period are again markedly different than during other periods. With low traffic volumes, it is more likely that “free flow” conditions occur more frequently overnight compared to other times of day.

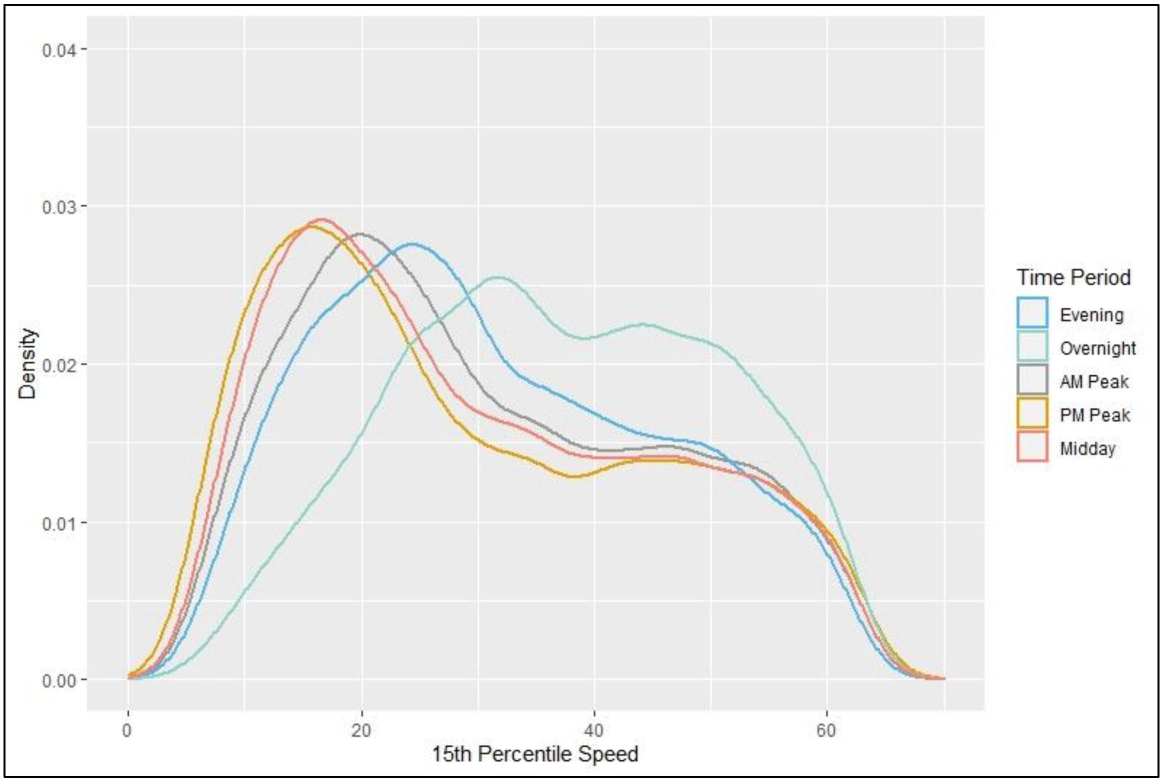

Figure 19. Line graph. Distribution of 15th percentile speeds by time of day.

Assuming TMCs during the morning peak have more congested periods than during other time periods, we modeled the relationship between speeds, speed differences, and crashes during these time periods. In table 17, the results of the AM peak model are displayed. The coefficients on higher speed differences (85th−median, 95th−5th, and 95th−85th) are notably smaller, ranging from 0.01 to 0.06. However, these metrics are still positive, significant, and larger in magnitude than the low-speed difference, which continues to range from −0.01 to 0.02. Table 18 displays results during the overnight period (24:00–5:59). Similar to the AM peak, the magnitudes of the coefficients on higher speed difference metrics are smaller than in other models, ranging from 0.01 to 0.08. The low-speed difference remains small relative to these metrics.

Table 15. Speed differences and crashes, AM Peak.

	Dependent Variable: Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.27	-0.68***	-0.62***	-0.30*	-0.65***	-0.67***	-0.66***	-0.51***
Speed Differences								
Low Speed Difference (Median−15th)	0.02***				-0.01	-0.003	-0.004	0.02***
High Speed Difference (85th−Median)		0.06***			0.06***	0.05***	0.06***	
Speed Dispersion (95th−5th)			0.04***			0.01		
Excessive Speed Differences (95th−85th)				0.05***			0.01	0.05***
Traffic Volume								
30–49,999 AADT	0.54***	0.50***	0.50***	0.53***	0.50***	0.50***	0.50***	0.52***
≥ 50,000 AADT	0.74***	0.67***	0.65***	0.68***	0.66***	0.66***	0.66***	0.69***
TMC Length								
Short TMC	-1.13***	-1.13***	-1.11***	-1.09***	-1.12***	-1.12***	-1.12***	-1.12***
Total TMC Length (miles)	0.27***	0.30***	0.30***	0.28***	0.30***	0.30***	0.30***	0.29***
Land Use Context								
Urban TMC	0.73***	0.68***	0.68***	0.69***	0.68***	0.68***	0.68***	0.70***
Rural TMC	-1.13***	-1.09***	-1.10***	-1.14***	-1.09***	-1.09***	-1.09***	-1.10***
Ecoregion								
Piedmont	0.07	0.10	0.09	0.05	0.10	0.10	0.10	0.08
Ridge and Valley	-0.36**	-0.30*	-0.31*	-0.36**	-0.31*	-0.31*	-0.31*	-0.33*
Southeastern Plain	-0.63***	-0.58***	-0.59***	-0.65***	-0.59***	-0.58***	-0.58***	-0.60***
Southern Coastal Plain	-0.46***	-0.40**	-0.41**	-0.47***	-0.41**	-0.40**	-0.40**	-0.43**
Observations	7,050	7,050	7,050	7,050	7,050	7,050	7,050	7,050
Log Likelihood	-11,415	-11,379	-11,383	-11,406	-11,378	-11,378	-11,378	-11,400

$^{+}p < 0.10$ *$p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 16. Speed differences and crashes, Overnight.

	Dependent Variable: Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-1.98***	-2.32***	-2.23***	-1.92***	-2.28***	-2.30***	-2.29***	-2.09***
Speed Differences								
Low Speed Difference (Median−15th)	0.02**				-0.01	-0.01	-0.01	0.02*
High Speed Difference (85th−Median)		0.07***			0.08***	0.06**	0.08***	
Speed Dispersion (95th–5th)			0.05***			0.02		
Excessive Speed Differences (95th–85th)				0.04***			0.01	0.04***
Traffic Volume								
30–49,999 AADT	0.21**	0.20**	0.21***	0.23***	0.20**	0.21**	0.20**	0.21***
≥ 50,000 AADT	0.32**	0.25*	0.27*	0.32**	0.25*	0.25*	0.25*	0.31**
TMC Length								
Short TMC	-1.74***	-1.68***	-1.68***	-1.71***	-1.67***	-1.67***	-1.67***	-1.72***
Total TMC Length (miles)	0.27***	0.29***	0.29***	0.28***	0.29***	0.29***	0.29***	0.28***
Land Use Context								
Urban TMC	1.06***	1.00***	1.00***	1.04***	1.00***	1.00***	1.00***	1.03***
Rural TMC	-0.70***	-0.70***	-0.71***	-0.73***	-0.71***	-0.71***	-0.71***	-0.70***
Ecoregion								
Piedmont	0.47*	0.48*	0.47*	0.47*	0.48*	0.47*	0.47*	0.47*
Ridge and Valley	0.06	0.10	0.09	0.06	0.10	0.10	0.10	0.07
Southeastern Plain	-0.01	0.02	0.01	-0.02	0.02	0.02	0.02	0.003
Southern Coastal Plain	0.40	0.44*	0.42	0.39	0.44*	0.44*	0.44*	0.40
Observations	4,336	4,336	4,336	4,336	4,336	4,336	4,336	4,336
Log Likelihood	-4,932	-4,915	-4,917	-4,929	-4,915	-4,914	-4,914	-4,927

$^{+}p < 0.10$ *$p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

CHAPTER 6 CONCLUSIONS

Assessing safety performance on roadway networks is difficult. Most transportation agencies and organizations use “hotspotting” to identify areas where an inordinate number of crashes occur. Crash data, while flawed, are regularly collected and mostly accurate. Areas where there are an extraordinarily high number of crashes are almost certainly more dangerous than other areas. However, there are gaps in the safety picture that crash data present due to the random occurrence of crashes, underreporting of crashes for certain roadway users, and many other factors. Therefore, it is important to use data to better understand some of the factors that have been shown to influence crashes, such as speed. Our analysis demonstrates a promising application of the NPMRDS speed data using speed percentile differences to approximate roadway risk.

Until very recently, few transportation organizations had access to regularly collected network-level vehicle speed data. Through the NPMRDS, Georgia DOT can monitor speeds on their roadway networks, and by extension safety on those networks. This is especially relevant on nonhighway road networks, where there is a greater variety of road users and contexts—a high number of intersections, interactions with pedestrians and cyclists, and potentially high differentials in vehicle speeds. However, there has been relatively little research on how to analyze regularly collected vehicle speed data on the network level to analyze safety outcomes. In addition, the NPMRDS speed data are very numerous and difficult to manipulate. While it is a potentially useful data source, it is necessary to reduce the data in a meaningful way for practitioners.

In each model run, the speed percentile values were significantly related to the expected number of crash outcomes. This was the case on the full network as well as when segmenting the data based on factors that might influence speed distributions and crash risk: traffic volume, time of day, TMC length, and only considering pedestrian and bicycle crashes. The consistent positive relationship across different iterations of models suggests that speed differences may be a useful operational metric. Conversely, examining individual percentiles alone yielded results that were counterintuitive and changed depending on which percentile values were included in models. Using only one percentile value is unlikely to inform practitioners about the overall safety on a particular roadway link. Several studies have noted that speed variation might be an appropriate indicator of risk on roadways (Solomon 1964, Lave 1985, and Kweon and Kockelman 2005). Newly available information in the NPMRDS provides extensive and timely data that can be used to calculate the dispersion of speed on road sections.

Typically, speed dispersion is measured using the standard deviation of speeds on a road network. This is a reasonable estimate of the dispersion of speeds; however, it suffers from several limitations. Standard deviation treats differences in high speeds the same as differences in lower speeds. It is likely that the higher speeds have a different influence on crash risk than lower speeds. Further, it is difficult for practitioners to understand what a one-unit increase in standard deviation means in practice. Rather than using these metrics of speed dispersion, we propose using a measure of speed difference. Our research assessed several options for measuring speed differences, each with a different application. First, we propose examining the “high-speed difference,” defined as the difference between the 85th percentile speed and the median speed. A second metric found to be related to increases in expected crash frequency on a roadway link is the difference between the 95th and 85th percentile speeds. Unlike the high-speed difference, the difference between the 95th and 85th percentile speeds is a metric of the most *excessive* speeders on a roadway link. This speed metric does not characterize the speed of the typical road users but notes when the highest speeds differ substantially from already high speeds.

In this research, both the high and excessive speed differences were significantly related to the frequency of crashes on the surface roadway network in Georgia. Importantly, the coefficients on speed difference have a practical interpretation. As the difference between 85th percentile speed and median speed, or the difference between the 95th and 85th percentile speed increases, the expected number of crashes per segment increases. Models including only one percentile speed yielded coefficients that were confusing (e.g., increasing percentiles at different levels could either increase or decrease the expected number of crashes). In addition, a change in only one percentile value may yield little information about overall speeds on the roadway section.

A third metric that was significantly related to crash frequency was the speed dispersion, defined as the difference between the 95th and 5th percentile speeds. The speed dispersion is a measure of the overall distribution of speeds. When there is a wider distribution of overall speeds, crashes are expected to occur. However, the speed dispersion is highly correlated with both the high-speed difference (0.91) and the excessive speed difference (0.87). While the speed dispersion is correlated with the low-speed difference, the correlation is weaker (0.44). The speed dispersion is most likely largest when high speeds are higher, rather than lower speeds being lower. Thus, using the overall speed dispersion, like the standard deviation of speeds, should be done in combination with metrics at the upper end of the speed distribution.

Understanding how the top-end speeds deviate could be more useful than simply understanding the median or average speed. For example, a congested roadway might exhibit a mean speed close to the posted speed limit because of high congestion at peak times (very low speeds), and very high speeds at free flow. Measuring the difference between speeds at the high end of the distribution would capture this effect in a way that a simple average or median would not. Further, different roadways are likely to exhibit different characteristics. Some roadways are meant to operate at higher speeds. Noting the median or average speed is higher is not necessarily indicative of a more dangerous road. However, noting that the top end of the speed distribution is disproportionally higher than other observed speeds on the roadway might suggest safety issues.

This research is the first to conflate speed, crash, and roadway attribute data in Georgia to test relationships between expected crashes and speeds; however, it has limitations. The availability of crash data, speed, and covariate data was limited to 2017. Future research should consider multiple years of data in order to test whether the estimated relationships between speed differences and crash frequency hold over time. Another limitation is that the outcome variable is "crashes," and distinguishing between severe and less severe crashes is difficult. When modeling reported injuries, the results do not change. High-end speed differences remain an important metric for determining where injuries occur, as the expected number of crashes per TMC and the expected number of injuries per TMC is highly correlated. However, estimating the severity of injury using speed differences is difficult. Fatal crashes account for less than 0.01 percent of crashes in this dataset, and it is difficult to model any expected relationship when so few TMCs experience crashes in a given year. Further, injuries and injury severity are assessed by police and reported in the crash record. While it is the best data available, reporting between agencies and even individual officers may be inconsistent. Improved data collection is necessary to assess injury severity as it relates to crashes at the network level. Despite these limitations, understanding where crashes and reported injuries are most likely to occur is an important step in identifying higher risk roadways and improving safety for all road users. Establishing safety performance metrics beyond crash counts is an important step in building a safer roadway system.

Safety performance metrics are limited by available data and tools to analyze it. With widely available speed data, it is possible to create improved, easy-to-interpret performance metrics for practitioners to apply on roadway networks. Crash reporting suffers from a substantial lag between the event and reporting, while regularly reported probe vehicle speed data are available to the Georgia Department of Transportation for an extensive network of roadways in close to real time. Creating safety performance metrics that can predict where crashes are most likely to occur is necessary to save lives and to allocate limited resources efficiently.

PROGRAM AND POLICY IMPLICATIONS

The statistical models developed in this research are useful only if they can be applied to real-world scenarios. In the following sections, we review potential applications of these metrics, and outline some key means of addressing safety problems once they are identified.

Probe Vehicle Speed Data as a Network Screening Tool

State and local governments are increasingly monitoring speeds on roadways as part of their safety performance evaluations. While this research was being conducted, the National Association of City Transportation Officials released its *City Limits* guidance and suggests using the standard deviation, median, 85th percentile, and 95th percentile speeds to assess corridor performance (City Limits 2020). Our research suggests that the percentile speeds cited in the NACTO guidance are important but should be evaluated in relation to one another. Speed differences are a relatively simple means of assessing the range of speeds experienced on a roadway, particularly at the higher end (85^{th}–median), as well as the range seen among the highest speed vehicles (95th–85th). NACTO's guidance notes the importance of speed dispersion by including the standard deviation as a potential speed metric (see figure 22). However, the standard deviation may overweight the influence of deviations on the lower end of the speed distribution. Similar results were reported by Elvik et al., where they demonstrated that a project may not substantially change the mean speed on a particular roadway, but it very well may change the top end speeds, which are likely related to serious and fatal injuries (Elvik et al. 2019).

Thus, the locations with the greater differences in the high-speed range would likely have received the most safety benefit from treatments that address these speed differences. It is therefore critical that any speed-based safety metric be able to identify these sites separately from low-end speed variation sites. Using metrics based on the higher portion of the speed distribution can add a critical element to the analysis of a project to determine whether crashes are more likely to decrease. By robustly assessing program effectiveness, departments of transportation can spend limited budgets more effectively, and scale up interventions that work.

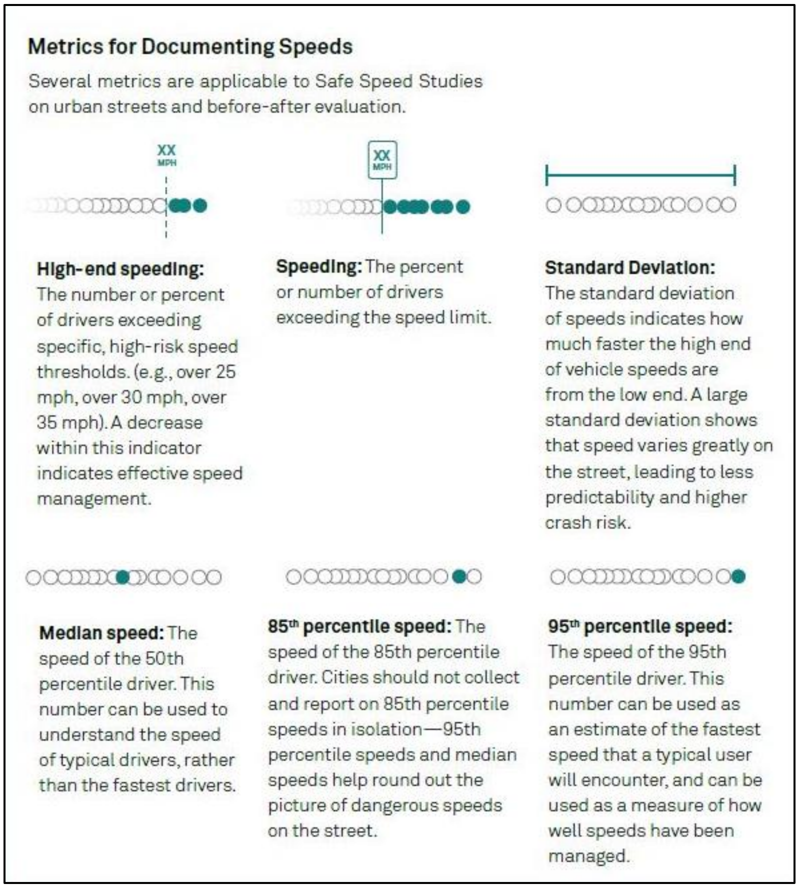

Figure 20. Chart. NACTO City Limits guidance on speed performance metrics.

Network Screening

Given the importance of speed differences in the higher speed range, a network evaluation approach can have several implications for transportation policy and practice. Typically, safety studies are not conducted until a high number of crashes occur in a particular location, an emotionally jarring event occurs, or if concerned citizens are organized and advocate for changes. Rather than relying on information about crashes that have already occurred, departments of transportation can proactively monitor their transportation networks and identify locations with potential speed-related safety issues before people are seriously injured or killed on the roadway.

Relying on crash data is reactive as safety issues are not identified until after crashes occur. In addition, crash data reporting can take several years. The public health approach prioritizes proactive measures and increasingly relies on real-time or close to real-time information. Speed-based metrics can be proactive, identifying potentially high-risk areas before crashes are reported. While speed data cannot replace crash data as a means of assessing safety, probe vehicle speed data can supplement crash-based network screening, potentially reducing the time window of crash data needed before mitigation actions may be taken.

For instance, safety performance metrics are reported quarterly at GDOT, and aggregated system-wide and regionally, including “Mileposts” performance measures on a quarterly basis (GDOT 2018). The current publicly reported safety mileposts are quarterly crash deaths, work zone deaths, and Highway Emergency Response Operators (HERO) response times. Speed-based network screening is complementary to these metrics, and could be reported internally for operations purposes. For example, a speed-based network screen could categorize roadway links having a “high,” “medium,” or “low” high-speed difference (85th−median). Corridors where the majority of TMCs are categorized as having higher high-speed differences may be identified for further analysis. Similarly, speed differences could be incorporated into dashboards, reports, and tools where probe speeds are already used to characterize roadway segments.

As with any metric, speed differences alone should not be the sole measure that is used for decision making. As our statistical models demonstrate, there are many factors that contribute to increased number of crashes on a given roadway. The amount of traffic, land use context, roadway design, and geographic location are all important considerations when assessing the level of safety. However, probe speed data may be used in addition to other information to determine when speed reduction and/or speed variability reduction may result in significant safety benefits.

Pilot Safety Studies to Assess Speed Difference Metrics Over Time and Validate Probe Speed Data

In addition to evaluating the roadways at the network level, probe speeds may be useful for evaluating specific safety projects. Our analysis of State Route 6 suggests that these data are useful at the corridor level in addition to the network level. When attempting to determine whether specific safety projects are successful or needed, speed differences could contribute another data point on which to make decisions.

Beyond established programs, probe-based speed data may be used for before-and-after project safety evaluations. Safety data for project evaluation are typically limited to crash counts. Where speed assessment is included, it is commonly in a limited before-and-after period (e.g., 2 months before implementation and 2 months after implementation). However, the wealth of probe data now available vastly expands the pool and time frame of potential speed data. Probe vehicle data are passively collected when substantial vehicle volumes are present, and archived for several years. Thus, probe vehicle speed data may be considered for additional baseline, and longer term follow-up data, capturing trends in the speed differences before and after a project. While probe vehicle speeds cannot singlehandedly replace crash and speed studies for projects, they are a useful tool for providing more insight on the project performance.

Incorporating Speed Operations

Probe speed data provides a promising source of data to identify where higher risk areas occur. After determining where there are problems in the roadway environment, we recommend that transportation professionals use the proposed Safe Systems Pyramid to identify which interventions should be prioritized. For example, if an area with high-speed differentials is identified, placing signage noting minimum and maximum speed limits would be a low priority intervention according to the Safe Systems Pyramid. It requires a high degree individual effort and does not change the built environment. According to the pyramid, changing signal timing to create a more uniform distribution of speeds would be preferable to simply adding signage. While this requires individual effort, the signal timing changes the context in which people operate and is thus more likely to result in people changing how they drive. A change to the built environment, such as adding a hardscaped median to reduce lane widths and add a safe pedestrian crossing point would be the highest priority intervention in the short term. No single intervention will solve all the problems in the roadway environment, and several levels of intervention may be necessary. Roadway contexts vary widely, and each treatment must be tailored to the context. The Safe Systems Pyramid can assist engineers and planners as they select interventions after identifying high risk areas.

There are several systematic methods for identifying interventions. Two specific areas that could use speed performance metrics and the Safe Systems Pyramid are road safety audits (RSAs) and the definition of "function" on a roadway.

FHWA defines road safety audits as "a formal safety performance examination of an existing or future road or intersection by an independent audit team" (FHWA 2006). RSAs are conducted to determine the nature of a safety problem on a roadway (e.g., excessive speed) and identify solutions to address the safety problem. RSAs may be completed during the design phase of a project. However, speed differences are most useful for audits of existing projects, as there is not sufficient research about the relationship between specific design elements and speed differences. FHWA's guidelines for RSAs does not include collecting any speed or crash data. In addition to those metrics already considered, the speed differences outlined in this report could be used to identify whether speed is one of the issues potentially contributing to crashes in the audited area. FHWA's RSA guidelines emphasize the need for a proactive, rather than a reactive approach (FHWA 2006). This is consistent with a public health consciousness. RSAs are an excellent means of identifying risk and can be supplemented by probe speed data. However, RSAs intentionally are not intended to rank or prioritize one project or another (FHWA 2006). Instead, other tools like the Safe Systems Pyramid can help engineers and planners do so. For example, should speed be identified as one of the issues on the corridor, practitioners should consult guidance on speed countermeasures specific to arterials, such as those in FHWA's *Countermeasures that Work* (FHWA 2019). The team evaluating this area could then list potential countermeasures appropriate for the context and use the Safe Systems Pyramid to rank them.

Along with incorporating speed into Road Safety Audits, departments of transportation should consider speeds other than the 85th percentile speed when developing designs and setting speed limits. Recent speed limit and design documents such as USLIMITS2 and *City Limits* suggest that the 50th percentile speed should be considered in addition to the 85th percentile speed when determining a design speed (Forbes et al. 2012, NACTO 2018). Our results suggest that considering both speed measurements is important. Thus, understanding the nature of a speed problem should involve examining the nature of the speed distribution, with a specific emphasis on the higher end of the speed distribution. The speed differences examined in this project are a useful means of analyzing portions of the speed distribution for safety studies.

Incorporating Speed into Design Guidance

Vehicle speed can be an important criterion for determining whether a roadway is accomplishing its intended purpose. For example, one might use vehicle volume data to determine whether or not a roadway carries the intended volume of traffic. Similarly, one could use probe speed data to determine whether vehicles on the roadway are traveling at the intended speed.

Speed limits are an important design criteria related to functional class. For example, GDOT’s Design Policy Manual currently states that rural arterials should have design speeds between 45 and 65 mph, and urban arterials should be from 45 to 55 mph, depending on the number of lanes and location in an urban or rural area (GDOT, 2020). Arterials are complex roadway environments that must serve local and regional traffic, a wide variety of land uses, and all road users. The current functional classification system emphasizes operating speed as it relates to vehicle volume with a strong emphasis on assigning a design speed and speed limit to carry a large amount of traffic (Laplante and McCann, 2008). Instead of considering a design speed as a secondary metric for vehicle volume, departments of transportation could consider whether speeds on the roadway are reflective of the intended speed and context.

Instead of thinking about function in terms of whether many vehicles move quickly on a facility, engineers and planners can use probe speed data to measure whether speeds on the roadway are appropriate for the context. If not, changes should be considered to the roadway. Under the traditional E’s approach, those changes might consist of encouraging drivers to slow down, or increasing enforcement if speeding is identified as an issue. The approach proposed in the Safe Systems Pyramid would suggest changes to the built environment to encourage drivers to move at a specific targeted speed.

“Target Speed” is an existing concept in transportation but could be better evaluated using probe vehicle speeds. The target speed is one of three metrics proposed to balance speed, mobility, and access on non-access limited facilities in NCHRP Report 855 titled *An Expanded Functional Classification System for Highways and Streets* (Stamatiadis et al. 2018). The concept of a target operating speed is used “to develop a facility where the operating speed is close to the design speed, resulting in an environment with smaller speed differences among drivers.” The report notes that creating target speeds is specifically intended to reduce speed differentials to “improve safety, since they will eliminate discrepancies between design speed and operating speeds, creating a more uniform speed profile among drivers” (Stamatiadis et al. 2018). The target speed is primarily based on roadway context. Determining roadway context requires creating several overlays to understand population density, access density, freight routes, transit routes, and mix of roads users (Stamatiadis et al. 2018). Depending on these factors, the target operating speed may be defined as low (<30 mph), medium (between 30 and 45 mph), or high (>45 mph). The target speed differs from the design speed in that it is a proactive measure, rather than reactive measure. In current practice, the posted speed limit can change in reaction to changes in the operating speed (NACTO 2018). In this approach, the posted speed limit can increase as the 85^{th} percentile speed increases (NACTO 2018). The target speed is proactive in that one designs for the speed which one would like drivers to travel at (NACTO 2018). Using probe vehicle speeds, it is possible to monitor whether people are driving at or close to the target speed. If people are traveling higher than the target speed, changes to the roadway should be made in order to bring operating speeds down.

This context sensitive approach allows for more flexibility to build roadways that are appropriate for the communities and businesses along these routes. With the wide variation in roads that departments of transportation manage and diversity of communities that they serve, a target operating speed could offer increased guidance to engineers while maintaining the flexibility needed to serve these communities.

At least one State Department of Transportation is taking target speed into account. Florida has a large network of roads managed by the State Department of Transportation (FDOT) and serves a mix of large cities, suburban areas, and small rural communities. FDOT adopted target speed in 2020 in its *Context Classification Guide* and defines target speed as "the highest speed at which vehicles should operate in a specific context, consistent with the level of multimodal activity generated by adjacent land uses, to provide both mobility for motor vehicles and a supportive environment for pedestrians, bicyclists, and public transit users (FDOT, 2020)." The Context Classification Guidance is based on both NCHRP 855 and context classification guidance in 2018 American Association of State Highway and Transportation Officials' Policy on Geometric Design of Highways and Streets (known as the "green book"). It is not meant to replace other guidance documents entirely but is meant to help engineers incorporate roadway context into their designs.

Notably, FDOT uses target speed retroactively to determine whether operating speeds exceed what is safe for the roadway context. Thus, the target speed can be retroactively applied to a roadway network to assist in prioritizing where modifications are needed. According to FDOT "The concept of target speed is to identify a desired operating speed and develop design strategies and elements that reinforce operating speeds consistent with the posted or proposed speed limit" (FDOT, 2020). In the same way that vehicle volume estimates are used to determine whether a road is achieving a specific Level of Service, the target speed can be used to determine whether it is operating at the specific level of safety. Probe vehicle speeds can be used to determine whether a roadway is exceeded the target speed.

Adopting a more detailed functional classification system and adopting a target speed as a metric may help better accommodate diverse needs in roadway environments. However, probe speed data may provide information on where operating speeds exceed the optimal speed for the roadway context. Roadway links where there are large speed differences between the 85th and median speed or 95th and 85th speed may indicate that modifications are needed to ensure that there is less variation in operating speeds.

As noted above, arterials are complex roadways that serve multiple purposes. However, limiting the highest speeds and speed differentials may limit the number of crashes and injuries. Using speed data to identify risk is a proactive means of determining risk of roadway networks. While using probe vehicle speed data is an important step in improving safety, crashes ultimately cannot be prevented without implementing countermeasures. Countermeasures should be evidence-based and built systematically in order to improve health and safety at the population level. The Safe Systems Pyramid proposed here can assist in identifying those countermeasures.

CHAPTER 7 RECOMMENDATIONS

Building safer roadways requires a systematic approach. Safer roadways have a myriad of public health benefits, including reducing the injuries and deaths that occur on roads. Public health principles that emphasize prevention and population-based approaches can be useful to transportation professionals as they attempt to build safer, healthier transportation systems. One of the key facets of the public health approach is to identify and limit key risk factors and promote protective factors. Speed is a key risk factor for traffic injuries and deaths. However, limiting the highest speeds and speed differentials may limit the number of crashes and injuries. In addition, areas where speed differentials are low may indicate the presence of engineered solutions that act as a protective factor. This research suggests that probe vehicle speeds may provide a useful tool for investigating safety problems in the future. Further, speed differences, especially those at the higher end of the speed distribution, are a promising means of measuring the speed distribution as it relates to safety. In this dissertation, we propose a framework for transportation safety based on public health principles and analyze the relationship between probe vehicle speed metrics and crashes over one year. Based on this analysis, we recommend that departments of transportation use this framework and consider using probe vehicle speed data and speed differences in their operations. We identified three broad recommendations:

1. Vision Zero programs should drop the E's framework in favor of the Safe Systems Pyramid
2. Use probe vehicle speed data, specifically differences in high-end speeds, as a network screening tool to identify locations where interventions may be needed.
3. Use speed differences in road safety audits and design guidance.

We have outlined how one might use the Safe Systems pyramid and noted how probe vehicle speeds may be used for network screening, before-and-after studies, and road safety audits. Each of these recommendations will need to be tailored to an individual department's processes and operations. Probe vehicle speeds are increasingly available and already used to assess metrics such as travel time. These data may also be used to assess safety on roadway networks through network screening (risk factor surveillance) and project evaluation. Incorporating probe speed data into performance measurement, and using speed differences to do so, can help determine what works in assessing their projects, communicate with policymakers and the public, and create a safer roadway system.

CHAPTER 8 FUTURE WORK

Early in this dissertation, we quote a 1931 editorial from the American Journal of Public Health defining public health engineering as "an essential calling, the prime object of which is to control the factors of the physical environment as they especially affect the health and welfare of aggregates of people" (Phelps 1931). This dissertation is the first of many attempts to bring transportation and public health practice in more close alignment. My future work will focus on how to promote collaboration between these fields, but more importantly, to bring the values of prevention and science-based interventions from public health into transportation engineering practice. We will contribute in the following ways:

1. Using new data to monitor transportation related health risks and outcomes: Probe vehicle speeds and other sources of speed data are increasingly available to state and local departments of transportation. To date, these data have been used to monitor travel times and congestion. Speed data and other new data sources can act as a "Syndromic Surveillance" system for road traffic injuries. Currently transportation departments are reactive, and only identify risky areas after serious injuries and deaths occur. Syndromic surveillance systems act as early warning systems that identify a preponderance of symptoms in a cluster of patients before an outbreak occurs. Extraordinarily high differences in speeds are symptoms of unsafe roads. In the same way that one can identify a flu outbreak by noting a preponderance of patients reporting high fever and shortness of breath; the symptoms of unsafe roads can be used to identify where intervention is needed. The performance metrics developed in this dissertation are a means of identifying risk on roadways. Using probe vehicle speeds and other emerging data sources, I will further develop, refine,

and test performance metrics for safer roads, physical activity, and exposure to noxious particulate matter.

2. Evaluating Safe Systems and Vision Zero policies: The Safe Systems approach, and Vision Zero policies are increasingly popular in the United States. However, there is little agreement on what those policies consist of, other than a commitment to zero roadway deaths and a focus on "speed." I will use the Safe Systems Pyramid to evaluate those policies, identifying whether the principles of injury prevention and control and risk management are inherent within those policies. The scientific basis for injury prevention and control and risk management has guided these fields and prevented countless unnecessary injuries and deaths. To accomplish goals for zero serious injuries and deaths, science must underly our policies. With a new paradigm shift towards Safe Systems, a new paradigm is needed in how to evaluate transportation safety. I plan to use the Safe Systems Pyramid to do so.
3. Applying risk management strategies to roadway design: One of the most successful interventions in transportation safety has been the application of the principles of injury prevention and control to vehicle design. By understanding that kinetic energy is the agent of injury, engineers designed vehicles to prevent the marshalling of force or distribute it over a larger area of the human body. The same ideas can be applied to the built environment. The Safe Systems Pyramid can be applied to transportation policies, but the principles of risk management inherent in the Hierarchy of Controls can be applied to engineering designs in the built environment. With the growth of automated and connected vehicles, there is promise in integrating safety frameworks that consider both vehicle and infrastructure interventions, and I plan to collaborate

across the built environment and vehicle design to develop models of different infrastructure designs to assess potential energy transferred in a crash.

Table 17. Negative binomial model of speed percentiles on injuries

	Dependent variable:							
	Injuries							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.934***	-1.034***	-1.230***	-1.420***	-1.499***	-1.472***	-1.587***	-1.664***
Percentile Speeds								
5th Percentile Speed	0.003						-0.018***	-0.063***
15th Percentile Speed		0.007**				-0.015		0.084***
50th Percentile Speed			0.010***			0.024	0.028**	-0.035
85th Percentile Speed				0.012***		0.002		0.020
95th Percentile Speed					0.013***		-0.0003	0.004
Traffic Volume (AADT)								
30-49,999 AADT	-0.064	-0.053	-0.048	-0.059	-0.067	-0.054	-0.046	-0.045
>= 50,000 AADT	-0.672**	-0.644**	-0.621**	-0.632**	-0.647**	-0.614**	-0.587**	-0.587**
TMC Length								
Short TMC	-0.881***	-0.866***	-0.874***	-0.887***	-0.893***	-0.904***	-0.914***	-0.882***
Total TMC Length (Miles)	0.317***	0.307***	0.302***	0.303***	0.305***	0.302***	0.298***	0.290***
Land Use Context								
Urban TMC	-0.101	-0.081	-0.063	-0.061	-0.065	-0.055	-0.045	-0.045
Rural TMC	-0.514***	-0.555***	-0.565***	-0.560***	-0.553***	-0.533***	-0.495***	-0.488***
Ecoregion								
Piedmont	-0.107	-0.140	-0.146	-0.139	-0.134	-0.119	-0.100	-0.118
Ridge and Valley	-0.186	-0.233	-0.247	-0.239	-0.230	-0.215	-0.196	-0.223
Southeastern Plains	-0.675***	-0.712***	-0.713***	-0.703***	-0.697***	-0.673***	-0.642***	-0.664***
Southern Coastal Plain	-0.713***	-0.742***	-0.745***	-0.734***	-0.727***	-0.714***	-0.689***	-0.697***
Observations	7,050	7,050	7,050	7,050	7,050	7,050	7,050	7,050
Log Likelihood	-5,729	-5,726	-5,723	-5,722	-5,722	-5,721	-5,716	-5,709
Note:								*p**p***p<0.001

Table 18. Negative binomial model of speed differences on injuries

	Dependent variable:							
	Injuries							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.77^{***}	0.31^{*}	0.30^{*}	0.66^{***}	0.32^{*}	0.25	0.27	0.42^{**}
Speed Differences								
Low Speed Difference (Median-15th)	0.02^{***}				-0.002	0.004	0.002	0.02^{***}
High Speed Difference (85th-median)		0.07^{***}			0.07^{***}	0.02	0.05^{***}	
Speed Dispersion (95th-5th)			0.05^{***}			0.04^{***}		
Excessive Speed Differences (95th-85th)				0.08^{***}			0.03^{***}	0.07^{***}
Traffic Volume (AADT)								
30-49,999	0.44^{***}	0.38^{***}	0.39^{***}	0.42^{***}	0.38^{***}	0.38^{***}	0.38^{***}	0.41^{***}
>= 50,000	0.54^{***}	0.42^{***}	0.39^{***}	0.43^{***}	0.41^{***}	0.39^{***}	0.40^{***}	0.45^{***}
TMC Length								
Short TMC	-0.98^{***}	-1.02^{***}	-1.01^{***}	-0.96^{***}	-1.01^{***}	-1.02^{***}	-1.02^{***}	-1.00^{***}
Total TMC Length (Miles)	0.27^{***}	0.30^{***}	0.30^{***}	0.29^{***}	0.30^{***}	0.30^{***}	0.30^{***}	0.29^{***}
Land Use Context								
Urban TMC	0.69^{***}	0.65^{***}	0.63^{***}	0.64^{***}	0.64^{***}	0.63^{***}	0.64^{***}	0.65^{***}
Rural TMC	-1.06^{***}	-0.97^{***}	-0.98^{***}	-1.04^{***}	-0.97^{***}	-0.97^{***}	-0.97^{***}	-1.01^{***}
Ecoregion								
Piedmont	-0.12	-0.06	-0.07	-0.14	-0.06	-0.06	-0.06	-0.10
Ridge and Valley	-0.47^{***}	-0.38^{**}	-0.39^{**}	-0.46^{***}	-0.38^{**}	-0.38^{**}	-0.38^{**}	-0.41^{**}
Southeastern Plains	-0.61^{***}	-0.55^{***}	-0.56^{***}	-0.64^{***}	-0.55^{***}	-0.55^{***}	-0.55^{***}	-0.58^{***}
Southern Coastal Plain	-0.56^{***}	-0.47^{***}	-0.49^{***}	-0.57^{***}	-0.47^{***}	-0.48^{***}	-0.48^{***}	-0.52^{***}
Observations	7,050	7,050	7,050	7,050	7,050	7,050	7,050	7,050
Log Likelihood	-16,046	-16,012	-16,006	-16,028	-16,011	-16,005	-16,008	-16,021
Note:								*p**p***p<0.001

Table 19. Results limited to only TMCs longer than 0.025 mile.

	Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	2.48***	2.83***	3.52***	4.14***	4.36***	3.29***	3.19***	3.07***
Percentile Speeds								
5th	-0.05***						-0.03***	-0.08***
15th		-0.04***				-0.03***		0.09***
50th			-0.05***			0.00	-0.02***	-0.08***
85th				-0.05***		-0.01		0.02
95th					-0.05***		0.00	-0.00
Traffic Volume (AADT)								
30–49,999	0.55***	0.54***	0.57***	0.61***	0.63***	0.56***	0.57***	0.57***
≥ 50,000	0.65***	0.58***	0.53***	0.60***	0.66***	0.57***	0.60***	0.59***
TMC Length								
Total (miles)	0.35***	0.36***	0.36***	0.34***	0.33***	0.36***	0.36***	0.35***
Land Use Context								
Urban	0.53***	0.50***	0.47***	0.46***	0.49***	0.48***	0.49***	0.49***
Rural	-0.70***	-0.73***	-0.80***	-0.89***	-0.93***	-0.75***	-0.71***	-0.69***
Ecoregion								
Piedmont	0.10	0.07	-0.03	-0.11	-0.14	0.03	0.05	0.04
Ridge and Valley	-0.12	-0.16	-0.28**	-0.38***	-0.43***	-0.20	-0.17	-0.19
Southeastern Plains	-0.43***	-0.49***	-0.64***	-0.74***	-0.77***	-0.55***	-0.51***	-0.53***
Southern Coastal Plain	-0.34***	-0.38***	-0.50***	-0.60***	-0.63***	-0.44***	-0.41***	-0.42***
Observations	6,269	6,269	6,269	6,269	6,269	6,269	6,269	6,269
Log Likelihood	-19,571	-19,575	-19,579	-19,630	-19,677	-19,560	-19,533	-19,506

$^{+}p < 0.10$ $^{*}p < 0.05$ $^{**}p < 0.01$ $^{***}p < 0.001$

Table 20. Differences in percentile speed models, limited to TMCs longer than 0.025.

	Dependent Variable = Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.96***	1.11***	0.99***	1.38***	1.22***	1.06***	1.08***	1.22***
Speed Differences								
Low Speed Difference (Median−15th)	0.02***				-0.02***	-0.01*	-0.01**	0.01**
High Speed Difference (85th−Median)		0.09***			0.11***	0.02	0.08***	
Speed Dispersion (95th−5th)			0.08***			0.07***		
Excessive Speed Differences (95th−85th)				0.15***			0.07***	0.15***
Traffic Volume (AADT)								
30–49,999	0.56***	0.47***	0.46***	0.49***	0.46***	0.45***	0.45***	0.48***
≥ 50,000	0.75***	0.57***	0.50***	0.53***	0.53***	0.48***	0.49***	0.54***
TMC Length								
Short TMC								
Total TMC Length (miles)	0.24***	0.28***	0.29***	0.27***	0.29***	0.29***	0.29***	0.27***
Land Use Context								
Urban	0.63***	0.60***	0.58***	0.57***	0.59***	0.57***	0.58***	0.58***
Rural	-1.28***	-1.12***	-1.11***	-1.19***	-1.12***	-1.11***	-1.11***	-1.17***
Ecoregion								
Piedmont	-0.19	-0.07	-0.08	-0.16	-0.10	-0.10	-0.10	-0.13
Ridge and Valley	-0.58***	-0.45***	-0.45***	-0.53***	-0.48***	-0.46***	-0.46***	-0.49***
Southeastern Plain	-0.82***	-0.68***	-0.69***	-0.79***	-0.71***	-0.71***	-0.71***	-0.75***
Southern Coastal Plain	-0.66***	-0.50***	-0.52***	-0.62***	-0.53***	-0.53***	-0.53***	-0.59***
Observations	6,269	6,269	6,269	6,269	6,269	6,269	6,269	6,269
Log Likelihood	-20,037	-19,935	-19,910	-19,952	-19,926	-19,908	-19,913	-19,948

$^{+}p < 0.10$ *$p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 21. Morning peak speed percentiles and crashes.

	Dependent Variable = Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.29*	0.51***	0.96***	1.35***	1.48***	0.79***	0.72***	0.67***
Percentile Speeds								
5th	-0.03***						-0.03***	-0.06***
15th		-0.03***				-0.03***		0.05***
50th			-0.03***			0.01	0.00	-0.04**
85th				-0.03***		-0.01		0.012
95th					-0.03***		-0.01*	-0.01
Traffic Volume (AADT)								
30–49,999	0.53***	0.51***	0.53***	0.56***	0.57***	0.52***	0.54***	0.55***
≥ 50,000	0.68***	0.64***	0.63***	0.66***	0.70***	0.64***	0.67***	0.69***
TMC Length								
Short TMC	-1.20***	-1.20***	-1.15***	-1.13***	-1.13***	-1.19***	-1.19***	-1.16***
Total TMC Length (miles)	0.36***	0.36***	0.36***	0.34***	0.33***	0.36***	0.36***	0.36***
Land Use Context								
Urban	0.62***	0.59***	0.57***	0.59***	0.61***	0.59***	0.60***	0.60***
Rural	-0.82***	-0.86***	-0.91***	-0.94***	-0.97***	-0.86***	-0.82***	-0.82***
Ecoregion								
Piedmont	0.28*	0.26*	0.19	0.16	0.14	0.25*	0.27*	0.25*
Ridge and Valley	-0.03	-0.04	-0.11	-0.17	-0.21	-0.05	-0.03	-0.06
Southeastern Plain	-0.35**	-0.39**	-0.47***	-0.53***	-0.56***	-0.40**	-0.38**	-0.39**
Southern Coastal Plain	-0.22	-0.24	-0.32*	-0.38**	-0.41**	-0.256*	-0.24	-0.25*
Observations	7,050	7,050	7,050	7,050	7,050	7,050	7,050	7,050
Log Likelihood	-11,241	-11,252	-11,262	-11,283	-11,299	-11,249	-11,233	-11,225

$^{+}p < 0.10$ *$p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 22. Morning peak speed differences and crashes.

	Dependent Variable							
	Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.27	-0.68***	-0.62***	-0.30*	-0.65***	-0.67***	-0.66***	-0.51***
Speed Differences								
Low Speed Difference (Median−15th)	0.02***				-0.01	-0.003	-0.004	0.02***
High Speed Difference (85th−Median)		0.06***			0.06***	0.05***	0.06***	
Speed Dispersion (95th−5th)			0.04***			0.01		
Excessive Speed Differences (95th−85th)				0.05***			0.01	0.05***
Traffic Volume (AADT)								
30–49,999 AADT	0.54***	0.50***	0.50***	0.53***	0.50***	0.50***	0.50***	0.52***
≥ 50,000 AADT	0.74***	0.67***	0.65***	0.68***	0.66***	0.66***	0.66***	0.69***
TMC Length								
Short TMC	-1.13***	-1.13***	-1.11***	-1.09***	-1.12***	-1.12***	-1.12***	-1.12***
Total TMC Length (miles)	0.27***	0.30***	0.30***	0.28***	0.30***	0.30***	0.30***	0.29***
Land Use Context								
Urban TMC	0.73***	0.68***	0.68***	0.69***	0.68***	0.68***	0.68***	0.70***
Rural TMC	-1.13***	-1.09***	-1.10***	-1.14***	-1.09***	-1.09***	-1.09***	-1.10***
Ecoregion								
Piedmont	0.07	0.10	0.09	0.05	0.10	0.10	0.10	0.08
Ridge and Valley	-0.36**	-0.30*	-0.31*	-0.36**	-0.31*	-0.31*	-0.31*	-0.33*
Southeastern Plain	-0.63***	-0.58***	-0.59***	-0.65***	-0.59***	-0.58***	-0.58***	-0.60***
Southern Coastal Plain	-0.46***	-0.40**	-0.41**	-0.47***	-0.41**	-0.40**	-0.40**	-0.43**
Observations	7,050	7,050	7,050	7,050	7,050	7,050	7,050	7,050
Log Likelihood	-11,415	-11,379	-11,383	-11,406	-11,378	-11,378	-11,378	-11,400

$^+p < 0.10$ *$p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 23. Midday crashes and speed percentiles.

	Dependent Variable = Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.79***	2.17***	2.95***	3.71***	3.95***	3.13***	2.97***	2.95***
Percentile Speeds								
5th	-0.05***						-0.02***	-0.06***
15th		-0.05***				-0.03***		0.06***
50th			-0.06***			0.01	-0.02***	-0.05***
85th				-0.06***		-0.04***		-0.02
95th					-0.06***		-0.02***	0.00
Traffic Volume (AADT)								
30–49,999	0.55***	0.53***	0.53***	0.56***	0.57***	0.55***	0.55***	0.56***
≥ 50,000	0.71***	0.63***	0.53***	0.53***	0.59***	0.57***	0.59***	0.59***
TMC Length								
Short TMC	-1.38***	-1.38***	-1.28***	-1.22**	-1.23***	-1.30***	-1.31***	-1.26***
Total TMC Length (miles)	0.36***	0.38***	0.37***	0.35***	0.33***	0.37***	0.37***	0.36***
Land Use Context								
Urban TMC	0.44***	0.40***	0.35***	0.33***	0.36***	0.35***	0.37***	0.36***
Rural TMC	-0.76***	-0.77***	-0.801***	-0.88***	-0.94***	-0.79***	-0.76***	-0.75***
Ecoregion								
Piedmont	-0.06	-0.08	-0.18	-0.28**	-0.32**	-0.16	-0.15	-0.16
Ridge and Valley	-0.26*	-0.29*	-0.40***	-0.51***	-0.58***	-0.37**	-0.34**	-0.35**
Southeastern Plain	-0.50***	-0.55***	-0.70***	-0.82***	-0.87***	-0.67***	-0.63***	-0.65***
Southern Coastal Plain	-0.46***	-0.50***	-0.65***	-0.77***	-0.82***	-0.63***	-0.59***	-0.61***
Observations	6,948	6,948	6,948	6,948	6,948	6,948	6,948	6,948
Log Likelihood	-15,407	-15,380	-15,342	-15,368	-15,428	-15,327	-15,315	-15,297

$^{+}p < 0.10$ $*p < 0.05$ $**\ p < 0.01$ $***\ p < 0.001$

Table 24. Midday crashes and speed differences.

	Dependent Variable = Crashes							
	Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.59***	0.76***	0.53***	0.77***	0.94***	0.75***	0.76***	0.87***
Speed Differences								
Low Speed Difference (Median−15th)	-0.01				-0.04***	-0.03***	-0.03***	-0.01
High Speed Difference (85th−Median)		0.07***			0.10***	-0.01	0.06***	
Speed Dispersion (95th−5th)			0.06***			0.08***		
Excessive Speed Differences (95th−85th)				0.13***			0.08***	0.13***
Traffic Volume (AADT)								
30–49,999 AADT	0.54***	0.52***	0.50***	0.50***	0.49***	0.48***	0.48***	0.49***
≥ 50,000 AADT	0.76***	0.76***	0.71***	0.67***	0.67***	0.64***	0.64***	0.66***
TMC Length								
Short TMC	-1.23***	-1.32***	-1.29***	-1.22***	-1.27***	-1.24***	-1.24***	-1.20***
Total TMC Length (miles)	0.23***	0.26***	0.27***	0.26***	0.27***	0.28***	0.28***	0.26***
Land Use Context								
Urban TMC	0.51***	0.52***	0.50***	0.49***	0.49***	0.48***	0.48***	0.48***
Rural TMC	-1.41***	-1.29***	-1.25***	-1.28***	-1.29***	-1.26***	-1.27***	-1.29***
Ecoregion								
Piedmont	-0.47***	-0.34**	-0.33**	-0.39***	-0.38***	-0.38***	-0.38***	-0.41***
Ridge and Valley	-0.87***	-0.71***	-0.69***	-0.75***	-0.76***	-0.74***	-0.74***	-0.77***
Southeastern Plain	-1.06***	-0.89***	-0.88***	-0.95***	-0.96***	-0.95***	-0.94***	-0.97***
Southern Coastal Plain	-0.97***	-0.79***	-0.78***	-0.86***	-0.85***	-0.84***	-0.84***	-0.88***
Observations	6,948	6,948	6,948	6,948	6,948	6,948	6,948	6,948
Log Likelihood	-15,904	-15,856	-15,823	-15,831	-15,826	-15,804	-15,810	-15,829

$^{+}p < 0.10$ *$p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 25. Evening peak speed percentiles and crashes.

	Dependent Variable = Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.30***	1.68***	2.36***	3.01***	3.22***	2.34***	2.18***	2.12***
Speed Percentiles								
5th	-0.05***						-0.03***	-0.07***
15th		-0.05***				-0.04***		0.07***
50th			-0.05***			0.01	-0.02**	-0.05***
85th				-0.05***		-0.03***		-0.01
95th					-0.05***		-0.01**	0.00
Traffic Volume (AADT)								
30–49,999 AADT	0.51***	0.48***	0.48***	0.54***	0.56***	0.50***	0.509***	0.518***
≥ 50,000 AADT	0.59***	0.51***	0.43***	0.47***	0.54***	0.48***	0.507***	0.499***
TMC Length								
Short TMC	-1.48***	-1.48***	-1.367***	-1.31***	-1.33***	-1.42***	-1.416***	-1.358***
Total TMC Length (miles)	0.36***	0.37***	0.37***	0.35***	0.33***	0.37***	0.373***	0.365***
Land Use Context								
Urban TMC	0.48***	0.44***	0.41***	0.42***	0.46***	0.42***	0.427***	0.429***
Rural TMC	-0.80***	-0.85***	-0.92***	-0.99***	-1.04***	-0.86***	-0.815***	-0.793***
Ecoregion								
Piedmont	0.12	0.07	-0.03	-0.11	-0.14	0.02	0.054	0.053
Ridge and Valley	-0.06	-0.10	-0.21	-0.31*	-0.35**	-0.15	-0.102	-0.114
Southeastern Plain	-0.38**	-0.44***	-0.58***	-0.69***	-0.72***	-0.51***	-0.462***	-0.467***
Southern Coastal Plain	-0.26*	-0.30*	-0.40***	-0.49***	-0.52***	-0.36**	-0.320**	-0.321**
Observations	6,586	6,586	6,586	6,586	6,586	6,586	6,586	6,586
Log Likelihood	-13,516	-13,510	-13,506	-13,548	-13,598	-13,486	-13,466	-13,450

$^{+}p < 0.10$ *$p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 26. Evening peak speed differences and crashes.

	Dependent Variable							
	Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.89^{***}	0.15	0.000	0.29^{*}	0.29^{*}	0.12	0.13	0.24
Speed Differences								
Low Speed Difference (Median−15th)	0.01				-0.03^{***}	-0.02^{**}	-0.02^{***}	0.004
High Speed Difference (85th−Median)		0.07^{***}			0.09^{***}	0.01	0.06^{***}	
Speed Dispersion (95th−5th)			0.06^{***}			0.06^{***}		
Excessive Speed Differences (95th−85th)				0.12^{***}			0.06^{***}	0.12^{***}
Traffic Volume (AADT)								
30–49,999 AADT	0.54^{***}	0.47^{***}	0.45^{***}	0.48^{***}	0.45^{***}	0.44^{***}	0.44^{***}	0.48^{***}
≥ 50,000 AADT	0.69^{***}	0.63^{***}	0.56^{***}	0.54^{***}	0.57^{***}	0.52^{***}	0.53^{***}	0.54^{***}
TMC Length								
Short TMC	-1.40^{***}	-1.46^{***}	-1.43^{***}	-1.37^{***}	-1.41^{***}	-1.40^{***}	-1.39^{***}	-1.38^{***}
Total TMC Length (miles)	0.24^{***}	0.27^{***}	0.28^{***}	0.27^{***}	0.28^{***}	0.28^{***}	0.28^{***}	0.27^{***}
Land Use Context								
Urban TMC	0.62^{***}	0.58^{***}	0.56^{***}	0.57^{***}	0.56^{***}	0.55^{***}	0.55^{***}	0.57^{***}
Rural TMC	-1.42^{***}	-1.30^{***}	-1.28^{***}	-1.33^{***}	-1.31^{***}	-1.30^{***}	-1.29^{***}	-1.32^{***}
Ecoregion								
Piedmont	-0.22	-0.11	-0.12	-0.19	-0.14	-0.15	-0.15	-0.18
Ridge and Valley	-0.60^{***}	-0.47^{***}	-0.47^{***}	-0.55^{***}	-0.50^{***}	-0.50^{***}	-0.50^{***}	-0.54^{***}
Southeastern Plain	-0.84^{***}	-0.71^{***}	-0.72^{***}	-0.80^{***}	-0.75^{***}	-0.75^{***}	-0.75^{***}	-0.79^{***}
Southern Coastal Plain	-0.63^{***}	-0.50^{***}	-0.51^{***}	-0.59^{***}	-0.52^{***}	-0.53^{***}	-0.53^{***}	-0.58^{***}
Observations	6,586	6,586	6,586	6,586	6,586	6,586	6,586	6,586
Log Likelihood	-13,941	-13,877	-13,854	-13,875	-13,865	-13,849	-13,851	-13,875

$^{+}p < 0.10$ $^{*}p < 0.05$ $^{**}p < 0.01$ $^{***}p < 0.001$

Table 27. Nighttime speed percentiles and crashes.

	Dependent Variable = Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.46**	0.78***	1.38***	1.87***	1.91***	1.12***	0.89***	0.72**
Speed Percentiles								
5th	-0.04***						-0.03***	-0.09**
15th		-0.04***				-0.02**		0.11***
50th			-0.04***			-0.02	-0.02**	-0.10***
85th				-0.04***		0.00		0.01
95th					-0.04***		0.00	0.02
Traffic Volume (AADT)								
30–49,999	0.39***	0.39***	0.43***	0.46***	0.46***	0.41***	0.41***	0.43***
≥ 50,000	0.64***	0.61***	0.60***	0.65***	0.67***	0.60***	0.61***	0.62***
TMC Length								
Short TMC	-1.22***	-1.19***	-1.06***	-1.05***	-1.08***	-1.12***	-1.15***	-1.03***
Total TMC Length (miles)	0.32***	0.33***	0.33***	0.32***	0.30***	0.333***	0.333***	0.32***
Land Use Context								
Urban TMC	0.34***	0.34***	0.30***	0.30***	0.34***	0.31***	0.31***	0.30***
Rural TMC	-0.81***	-0.90***	-0.95***	-0.98***	-1.01***	-0.92***	-0.85***	-0.78***
Ecoregion								
Piedmont	0.18	0.11	0.06	0.02	0.01	0.09	0.14	0.18
Ridge and Valley	0.03	-0.04	-0.10	-0.16	-0.20	-0.06	0.00	0.04
Southeastern Plain	-0.25	-0.34*	-0.42*	-0.46**	-0.47**	-0.37*	-0.30	-0.27
Southern Coastal Plain	-0.17	-0.24	-0.30	-0.35*	-0.36*	-0.27	-0.21	-0.18
Observations	4,289	4,289	4,289	4,289	4,289	4,289	4,289	4,289
Log Likelihood	-6,838	-6,848	-6,847	-6,867	-6,892	-6,842	-6,828	-6,807

$^{+}p < 0.10$ $^{*}p < 0.05$ $^{**}p < 0.01$ $^{***}p < 0.001$

Table 28. Nighttime speed differences and crashes.

	Dependent Variable							
	Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-0.36	-1.01***	-1.01***	-0.55**	-0.89***	-0.96***	-0.94***	-0.69***
Speed Differences								
Low Speed Difference (Median−15th)	0.02**				-0.02**	-0.02*	-0.02*	0.01*
High Speed Difference (85th−Median)		0.09***			0.11***	0.06***	0.09***	
Speed Dispersion (95th−5th)			0.07***			0.03**		
Excessive Speed Differences (95th−85th)				0.09***			0.03**	0.09***
Traffic Volume (AADT)								
30–49,999	0.37***	0.33***	0.35***	0.39***	0.34***	0.35***	0.35***	0.38***
≥ 50,000	0.71***	0.59***	0.60***	0.66***	0.57***	0.57***	0.57***	0.66***
TMC Length								
Short TMC	-1.16***	-1.12***	-1.06***	-1.05***	-1.05***	-1.04***	-1.04***	-1.09***
Total TMC Length (miles)	0.23***	0.26***	0.27***	0.25***	0.27***	0.27***	0.27***	0.25***
Land Use Context								
Urban TMC	0.54***	0.51***	0.50***	0.50***	0.50***	0.49***	0.49***	0.50***
Rural TMC	-1.14***	-1.09***	-1.10***	-1.15***	-1.11***	-1.11***	-1.11***	-1.12***
Ecoregion								
Piedmont	-0.01	0.03	0.02	-0.02	0.01	0.01	0.01	-0.005
Ridge and Valley	-0.31	-0.23	-0.24	-0.30	-0.25	-0.24	-0.24	-0.27
Southeastern Plains	-0.52**	-0.47**	-0.50**	-0.56***	-0.50**	-0.50**	-0.50**	-0.53**
Southern Coastal Plain	-0.37*	-0.30	-0.33	-0.38*	-0.32	-0.32	-0.32	-0.35*
Observations	4,289	4,289	4,289	4,289	4,289	4,289	4,289	4,289
Log Likelihood	-7,001	-6,955	-6,953	-6,980	-6,951	-6,947	-6,948	-6,978

$^{+}p < 0.10$ *$p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 29. Overnight speed percentiles and crashes.

	Dependent Variable = Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-1.15***	-0.88***	-0.32	0.12	0.137	-0.31	-0.46	-0.42
Percentile Speed								
5th	-0.03***						-0.01*	-0.05***
15th		-0.03***				0.00		0.07***
50th			-0.04***			-0.03	-0.02**	-0.08**
85th				-0.04***		0.00		0.00
95th					-0.04***		0.03	0.00
Traffic Volume (AADT)								
30–49,999	0.22***	0.231***	0.262***	0.28***	0.28***	0.26***	0.25***	0.26***
≥ 50,000	0.28*	0.270*	0.286*	0.33**	0.34**	0.29*	0.28*	0.30*
TMC Length								
Short TMC	-1.70***	-1.659***	-1.623***	-1.64***	-1.66***	-1.62***	-1.64***	-1.65***
Total TMC Length (miles)	0.32***	0.333***	0.341***	0.34***	0.33***	0.34***	0.34***	0.34***
Land Use Context								
Urban TMC	0.867***	0.85***	0.82***	0.83***	0.87***	0.82***	0.82***	0.81***
Rural TMC	-0.55***	-0.60***	-0.63***	-0.63***	-0.64***	-0.63***	-0.59***	-0.55***
Ecoregion								
Piedmont	0.63**	0.61**	0.63**	0.64**	0.63**	0.63**	0.64**	0.67**
Ridge and Valley	0.35	0.35	0.37	0.36	0.32	0.37	0.39	0.41
Southeastern Plain	0.24	0.21	0.22	0.21	0.17	0.22	0.24	0.27
Southern Coastal Plain	0.58**	0.56*	0.57**	0.56*	0.53*	0.57**	0.59**	0.61**
Observations	4,336	4,336	4,336	4,336	4,336	4,336	4,336	4,336
Log Likelihood	-4,867	-4,866	-4,858	-4,863	-4,875	-4,858	-4,856	-4,849

$^{+}p < 0.10$ *$p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Table 30. Overnight speed differences and crashes.

	Dependent Variable							
	Crashes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-1.98***	-2.32***	-2.23***	-1.92***	-2.28***	-2.30***	-2.29***	-2.09***
Speed Difference								
Low Speed Difference (Median−15th)	0.02**				-0.01	-0.01	-0.01	0.02*
High Speed Difference (85th−Median)		0.07***			0.08***	0.06**	0.08***	
Speed Dispersion (95th−5th)			0.05***			0.02		
Excessive Speed Differences (95th−85th)				0.04***			0.01	0.04***
Traffic Volume (AADT)								
30–49,999	0.21**	0.20**	0.21***	0.23***	0.20**	0.21**	0.20**	0.21***
≥ 50,000	0.32**	0.25*	0.27*	0.32**	0.25*	0.25*	0.25*	0.31**
TMC Length								
Short TMC	-1.74***	-1.68***	-1.68***	-1.71***	-1.67***	-1.67***	-1.67***	-1.72***
Total TMC Length (miles)	0.27***	0.29***	0.29***	0.28***	0.29***	0.29***	0.29***	0.28***
Land Use Context								
Urban TMC	1.06***	1.00***	1.00***	1.04***	1.00***	1.00***	1.00***	1.03***
Rural TMC	-0.70***	-0.70***	-0.71***	-0.73***	-0.71***	-0.71***	-0.71***	-0.70***
Ecoregion								
Piedmont	0.47*	0.48*	0.47*	0.47*	0.48*	0.47*	0.47*	0.47*
Ridge and Valley	0.06	0.10	0.09	0.06	0.10	0.10	0.10	0.07
Southeastern Plain	-0.01	0.02	0.01	-0.02	0.02	0.02	0.02	0.003
Southern Coastal Plain	0.40	0.44*	0.42	0.39	0.44*	0.44*	0.44*	0.40
Observations	4,336	4,336	4,336	4,336	4,336	4,336	4,336	4,336
Log Likelihood	-4,932	-4,915	-4,917	-4,929	-4,915	-4,914	-4,914	-4,927

$^{+}p < 0.10$ $^{*}p < 0.05$ $^{**}p < 0.01$ $^{***}p < 0.001$

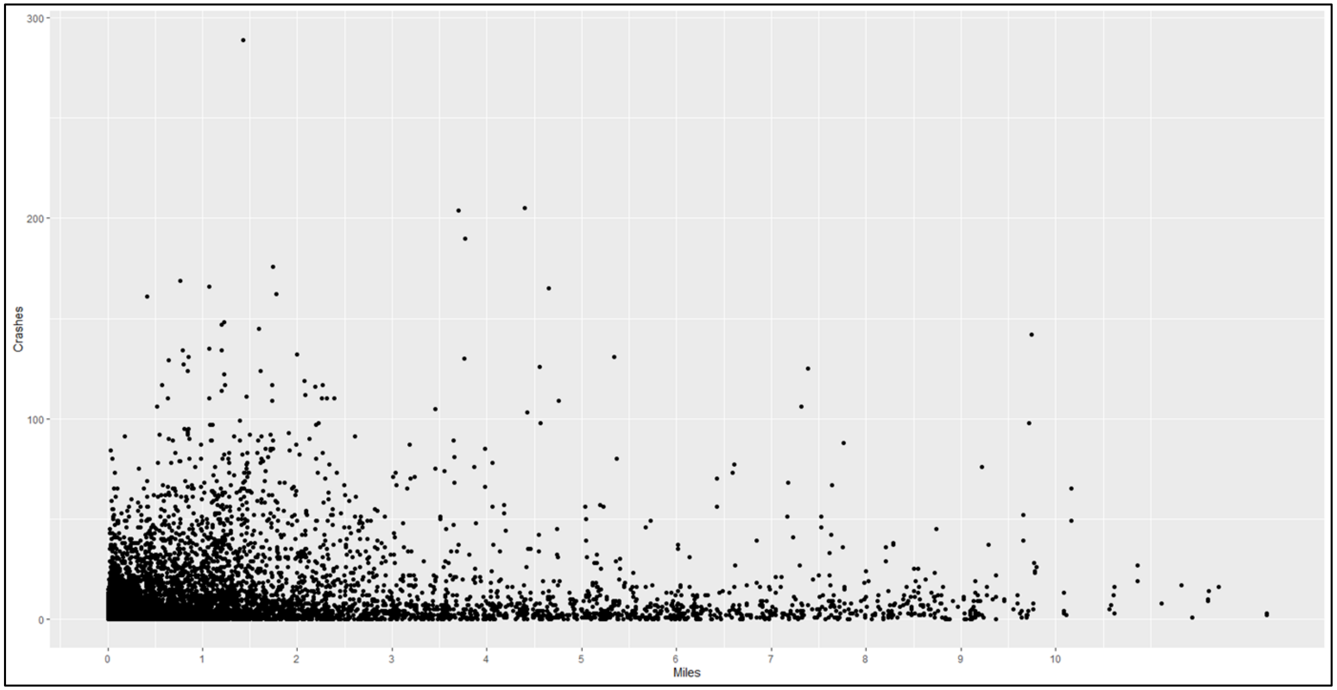

Figure 21. Scatterplot. TMC length and number of crashes in 2017.

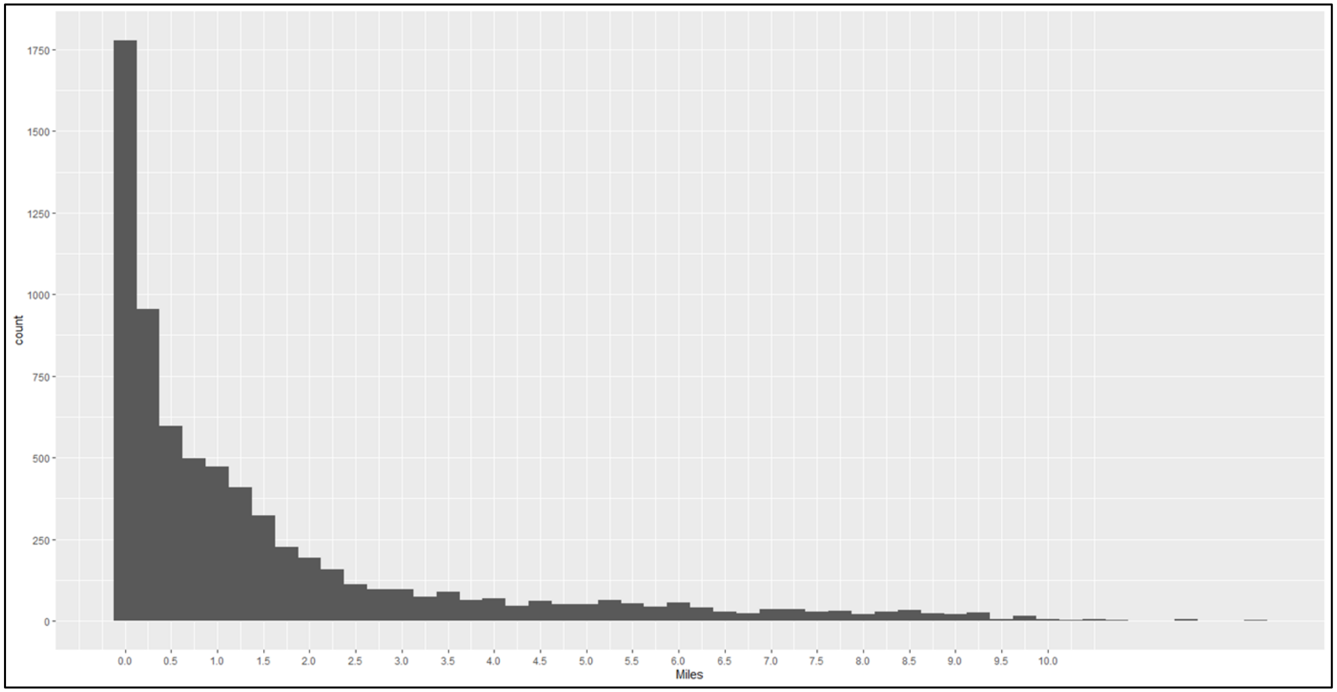

Figure 22. Histogram. TMC lengths (miles).

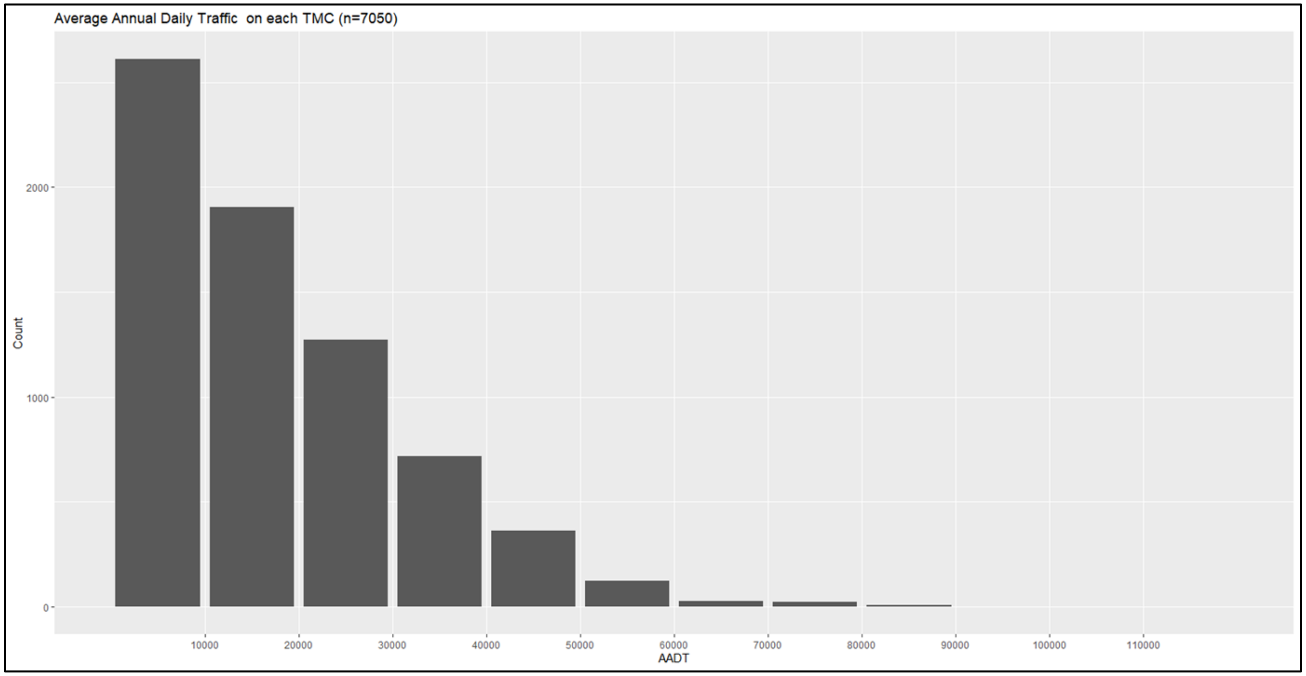

Figure 23. Bar chart. Crashes per TMC by AADT range.

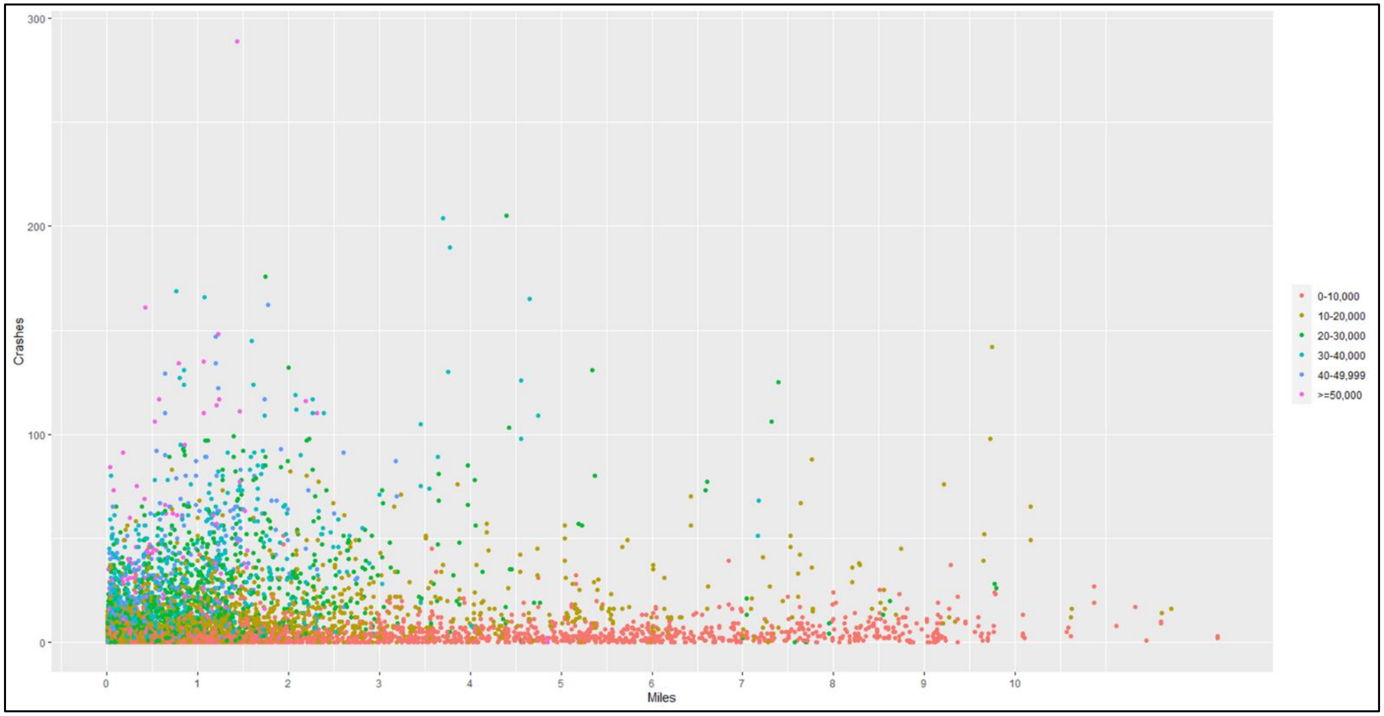

Figure 24. Scatterplot. Crashes per TMC in relation to TMC length and AADT category.

Table 31. Correlation table of all variables in analysis (correlations greater than |0.7| highlighted in yellow).

		Percentiles					Speed Differences				Control Variables							Outcomes	
		5th	15th	50th	85th	95th	50^{th}–15^{th}	85^{th}–50^{th}	95^{th}–5^{th}	95^{th}–85^{th}	AADT	Short TMC	Miles	PSL	Urban	Small Urban	Rural	Crashes	Injuries
Percentiles	5th	1.00	0.98	0.93	0.88	0.84	-0.58	-0.76	-0.71	-0.49	-0.45	-0.20	0.52	0.72	-0.51	-0.05	0.61	-0.27	-0.19
	15th	0.98	1.00	0.97	0.93	0.89	-0.49	-0.77	-0.73	-0.52	-0.47	-0.20	0.55	0.76	-0.52	-0.03	0.61	-0.27	-0.18
	50th	0.93	0.97	1.00	0.98	0.95	-0.27	-0.70	-0.69	-0.52	-0.46	-0.17	0.54	0.81	-0.51	-0.02	0.58	-0.28	-0.19
	85th	0.88	0.93	0.98	1.00	0.98	-0.16	-0.54	-0.56	-0.45	-0.41	-0.15	0.51	0.85	-0.48	-0.02	0.56	-0.27	-0.18
	95th	0.84	0.89	0.95	0.98	1.00	-0.12	-0.46	-0.42	-0.27	-0.37	-0.14	0.49	0.84	-0.45	-0.03	0.53	-0.25	-0.17
Speed Differences	Low Speed	-0.58	-0.49	-0.27	-0.16	-0.12	1.00	0.57	0.44	0.21	0.22	0.18	-0.23	-0.09	0.22	0.08	-0.31	0.07	0.07
	High Speed	-0.76	-0.77	-0.70	-0.54	-0.46	0.57	1.00	0.91	0.60	0.46	0.20	-0.45	-0.39	0.43	-0.01	-0.47	0.20	0.14
	Speed Dispersion	-0.71	-0.73	-0.69	-0.56	-0.42	0.44	0.91	1.00	0.87	0.44	0.18	-0.43	-0.41	0.42	-0.03	-0.44	0.21	0.15
	Excess Speed	-0.49	-0.52	-0.52	-0.45	-0.27	0.21	0.60	0.87	1.00	0.32	0.11	-0.32	-0.35	0.32	-0.04	-0.32	0.17	0.12
Covariates	AADT	-0.45	-0.47	-0.46	-0.41	-0.37	0.22	0.46	0.44	0.32	1.00	0.07	-0.33	-0.25	0.62	-0.22	-0.50	0.44	0.36
	Short TMC	-0.20	-0.20	-0.17	-0.15	-0.14	0.18	0.20	0.18	0.11	0.07	1.00	-0.25	-0.13	0.11	-0.01	-0.11	-0.13	-0.14
	Miles	0.52	0.55	0.54	0.51	0.49	-0.23	-0.45	-0.43	-0.32	-0.33	-0.25	1.00	0.47	-0.36	-0.08	0.47	0.05	0.10
	PSL	0.72	0.76	0.81	0.85	0.84	-0.09	-0.39	-0.41	-0.35	-0.25	-0.13	0.47	1.00	-0.36	-0.05	0.44	-0.15	-0.09
	Urban	-0.51	-0.52	-0.51	-0.48	-0.45	0.22	0.43	0.42	0.32	0.62	0.11	-0.36	-0.36	1.00	-0.51	-0.66	0.33	0.29
	Small Urban	-0.05	-0.03	-0.02	-0.02	-0.03	0.08	-0.01	-0.03	-0.04	-0.22	-0.01	-0.08	-0.05	-0.51	1.00	-0.31	-0.12	-0.11
	Rural	0.61	0.61	0.58	0.56	0.53	-0.31	-0.47	-0.44	-0.32	-0.50	-0.11	0.47	0.44	-0.66	-0.31	1.00	-0.26	-0.22
Outcome	Crashes	-0.27	-0.27	-0.28	-0.27	-0.25	0.07	0.20	0.21	0.17	0.44	-0.13	0.05	-0.15	0.33	-0.12	-0.26	1.00	0.86
	Injuries	-0.19	-0.18	-0.19	-0.18	-0.17	0.07	0.14	0.15	0.12	0.36	-0.14	0.10	-0.09	0.29	-0.11	-0.22	0.86	1.00

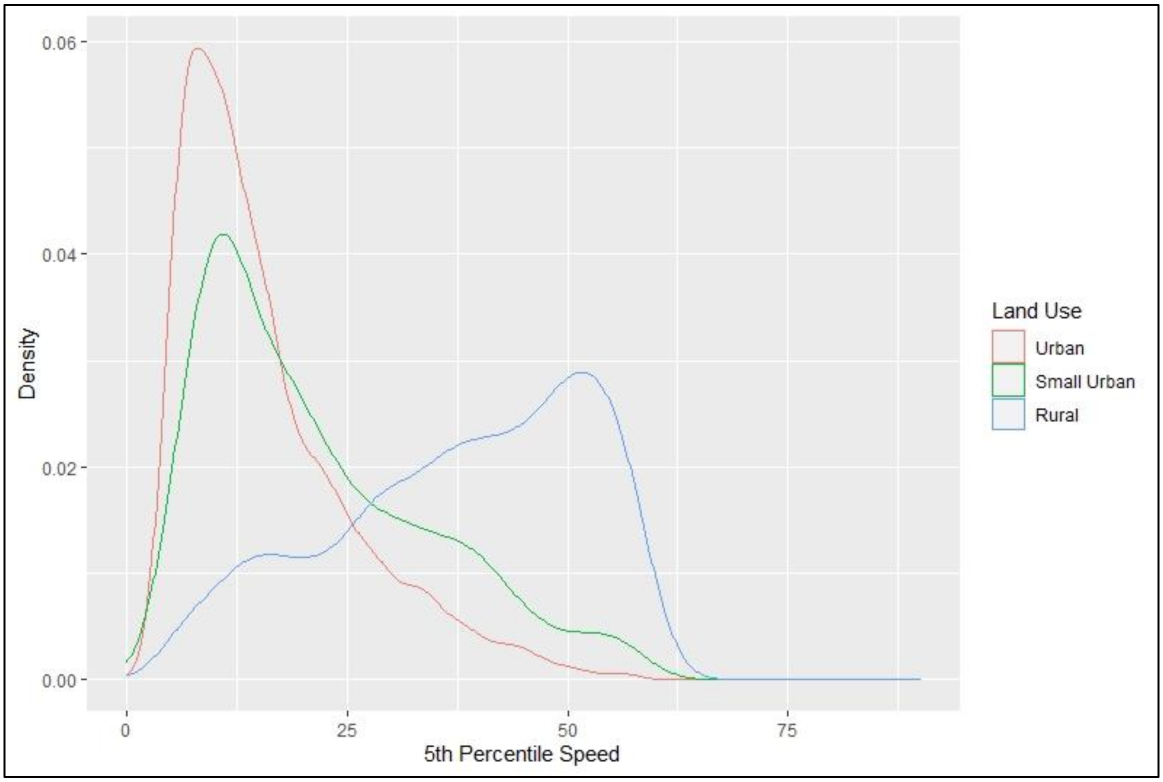

Figure 25. Line graph. Distribution of 5th percentile speeds per TMC by land use.

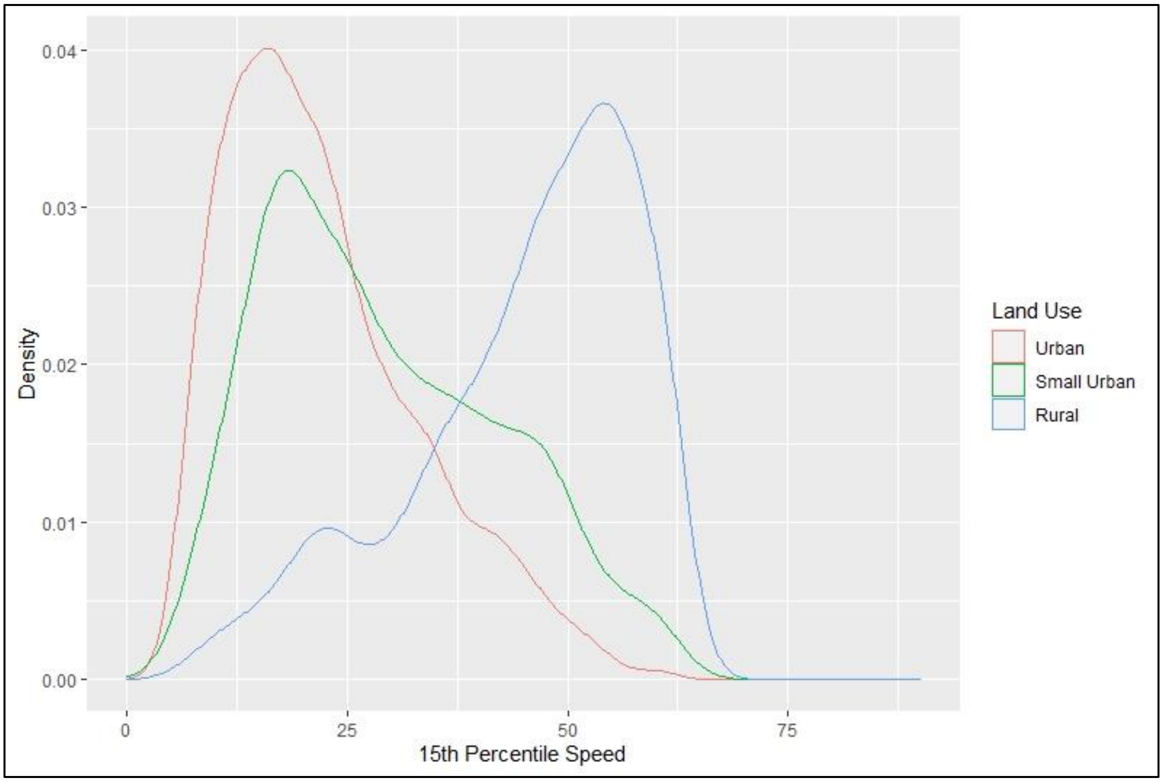

Figure 26. Line graph. Distribution of 15th percentile speeds per TMC by land use.

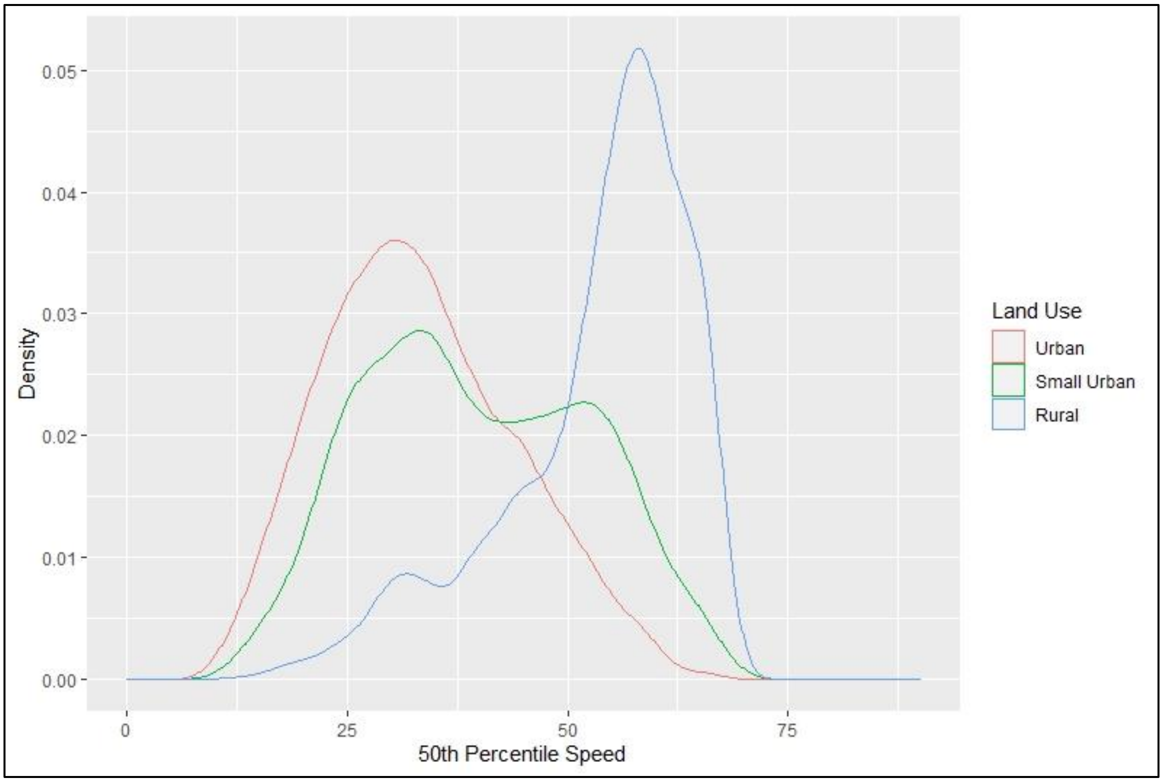

Figure 27. Line graph. Distribution of 50th percentile speeds per TMC by land use.

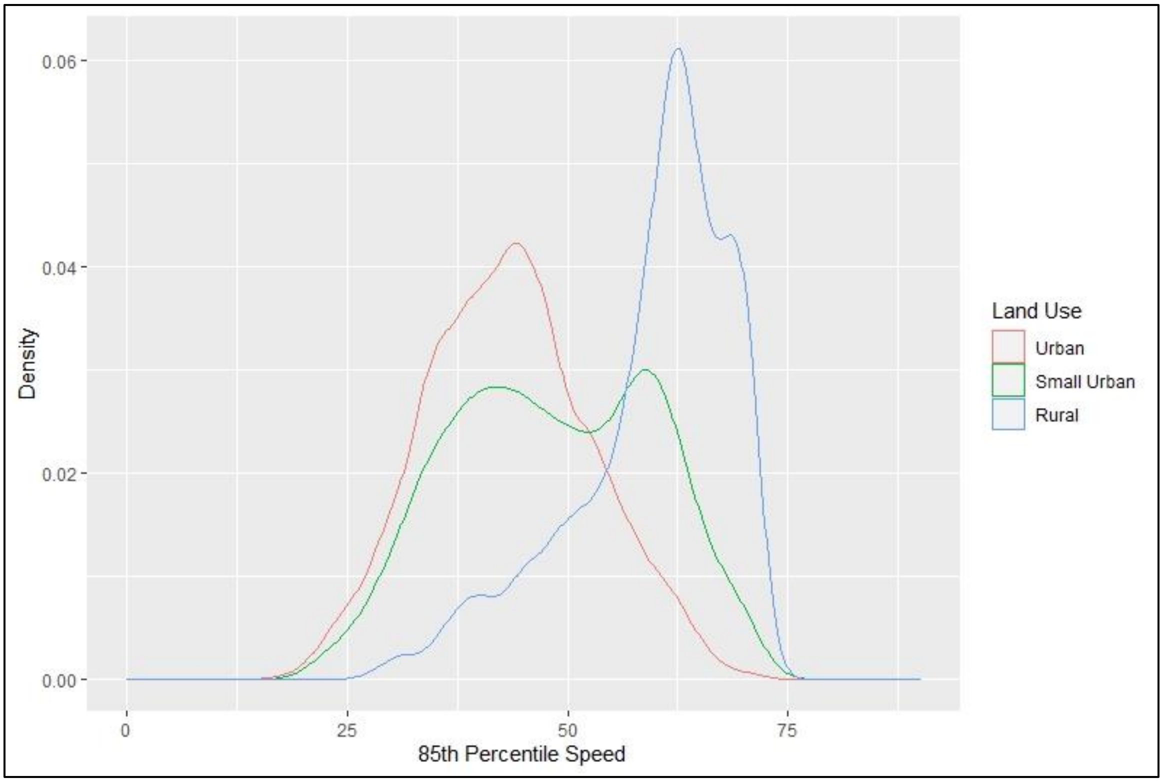

Figure 28. Line graph. Distribution of 85th percentile speeds per TMC by land use.

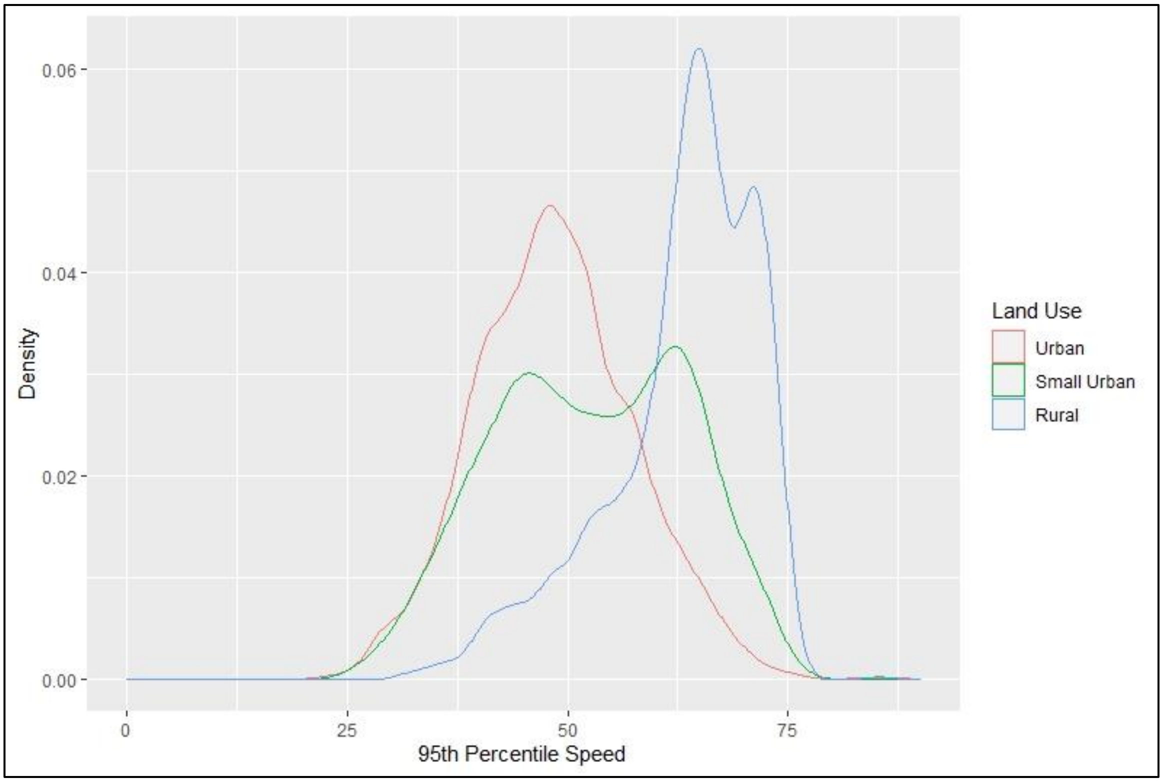

Figure 29. Line graph. Distribution of 95th percentile speeds per TMC by land use.

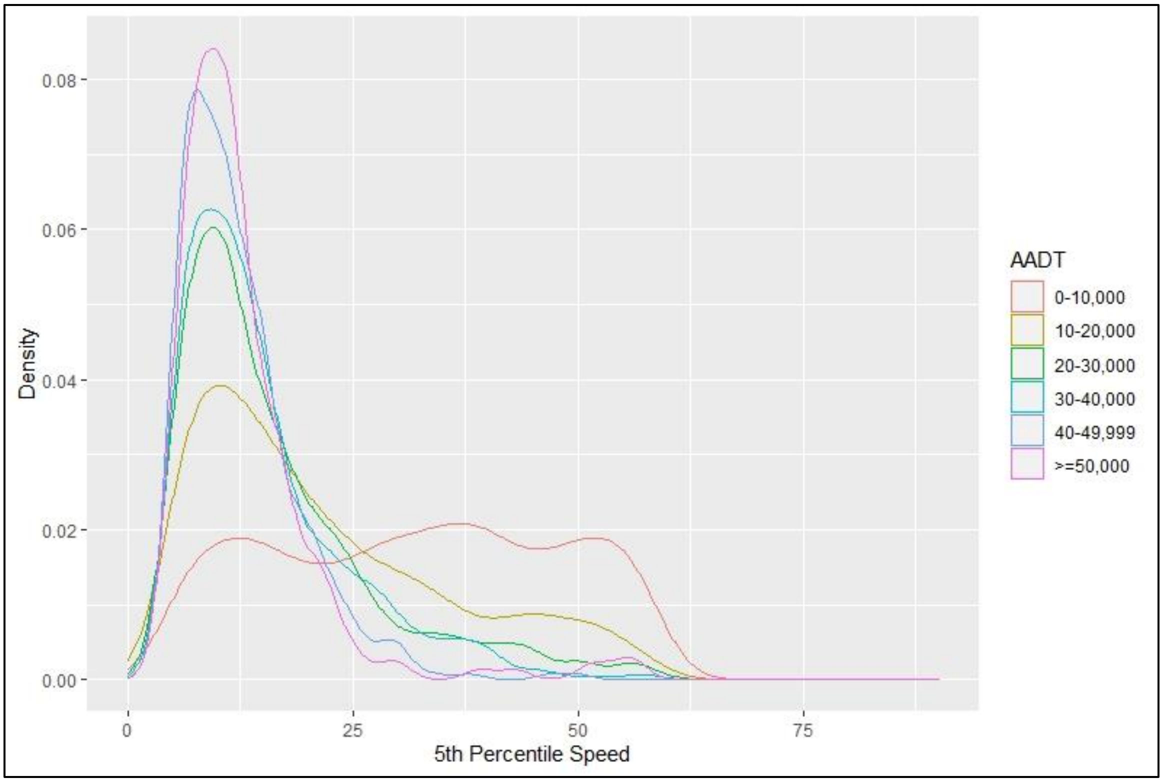

Figure 30. Line graph. Distribution of 5th percentile speeds per TMC by AADT.

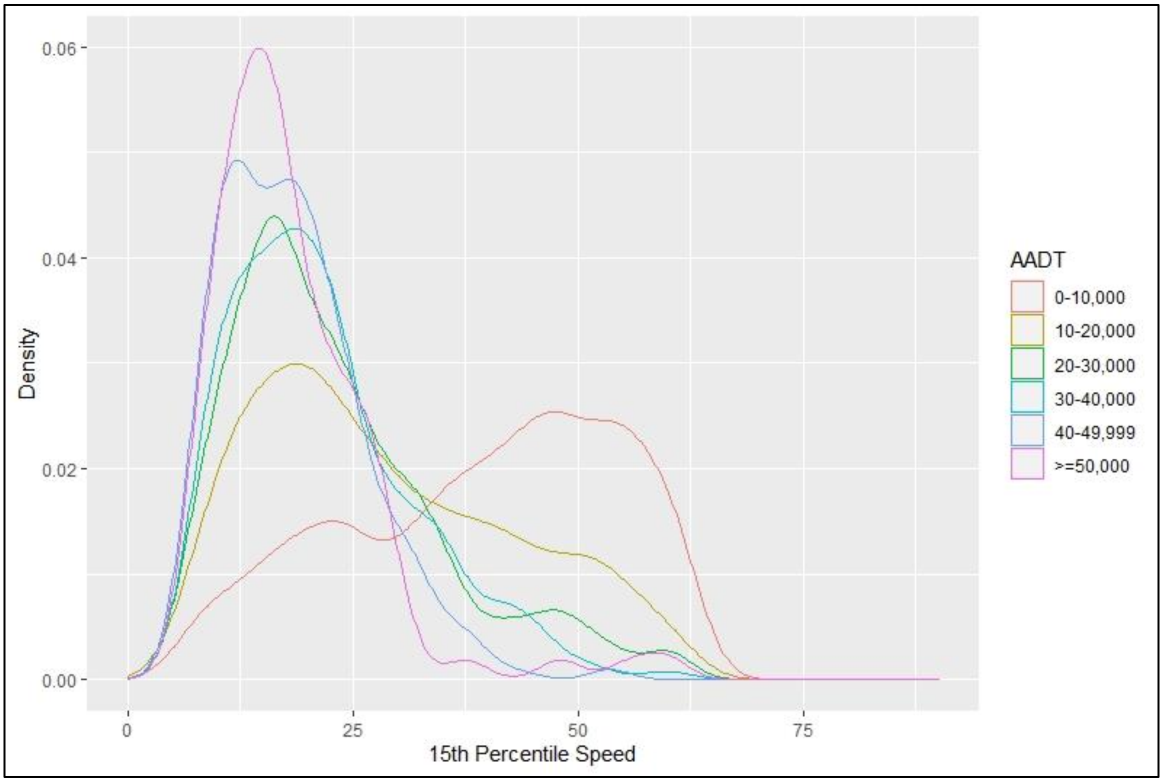

Figure 31. Line graph. Distribution of 15th percentile speeds per TMC by AADT.

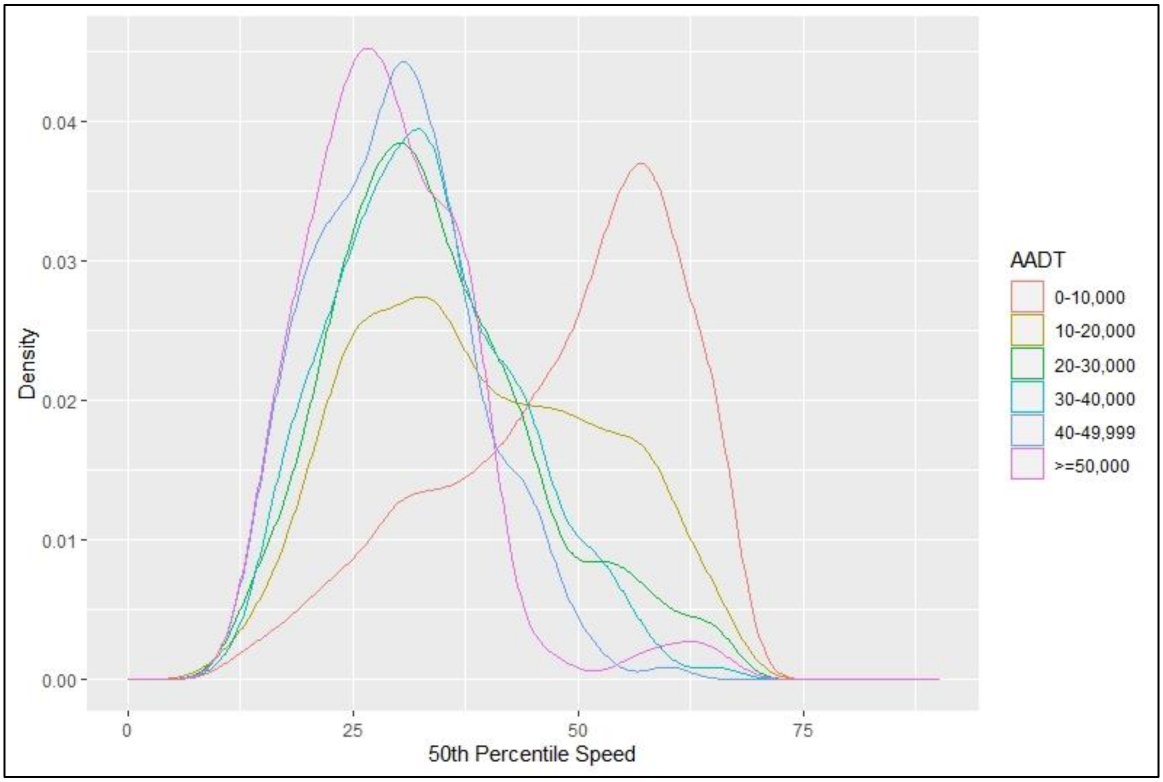

Figure 32. Line graph. Distribution of 50th percentile speeds per TMC by AADT.

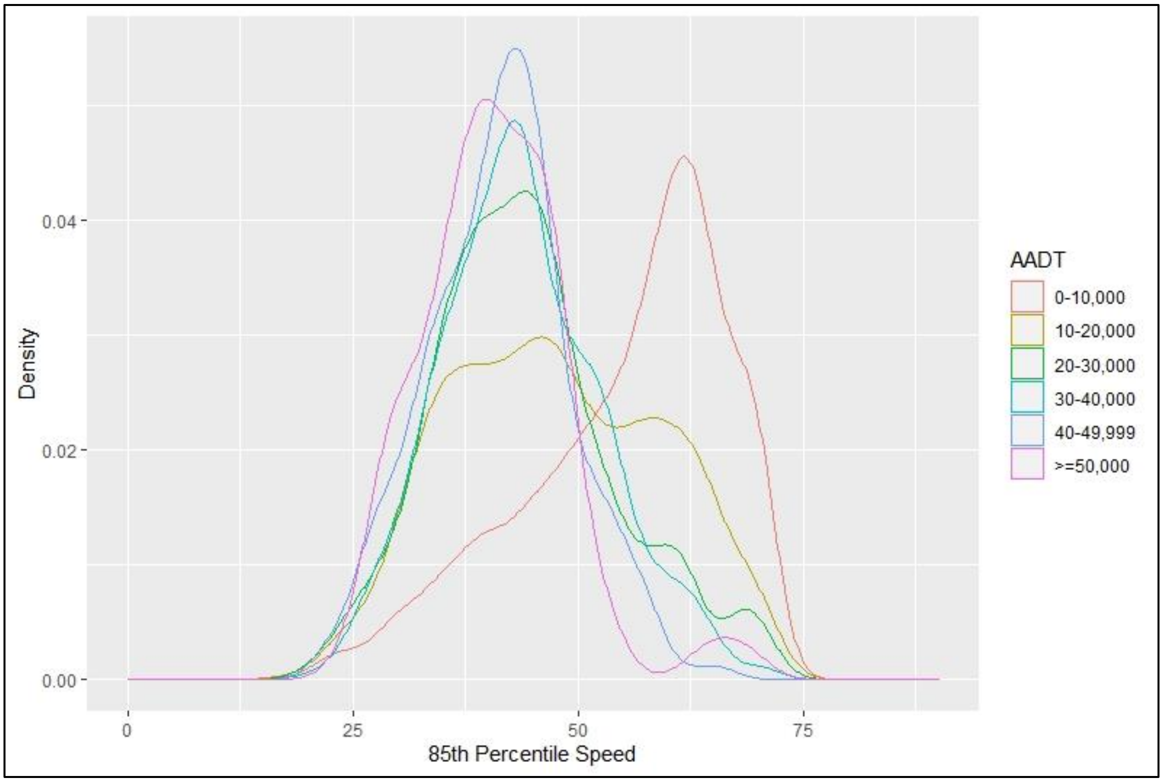

Figure 33. Line graph. Distribution of 85th percentile speeds per TMC by AADT.

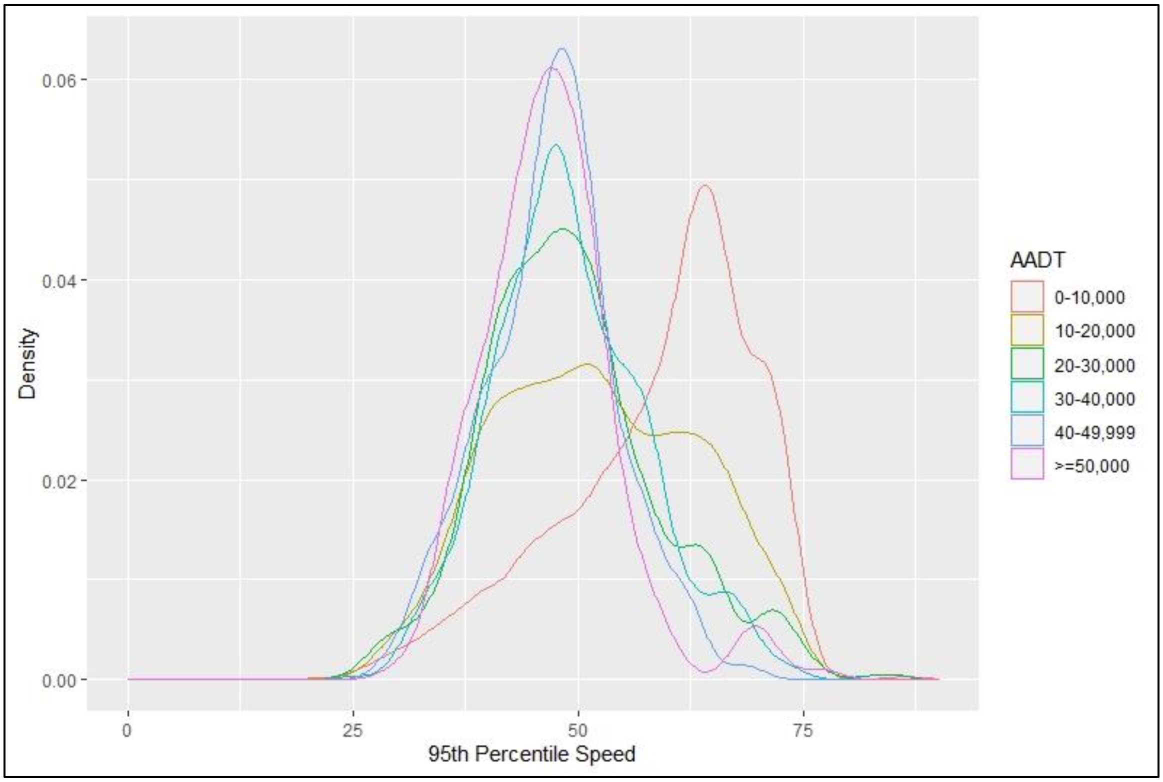

Figure 34. Line graph. Distribution of 95th percentile speeds per TMC by AADT.

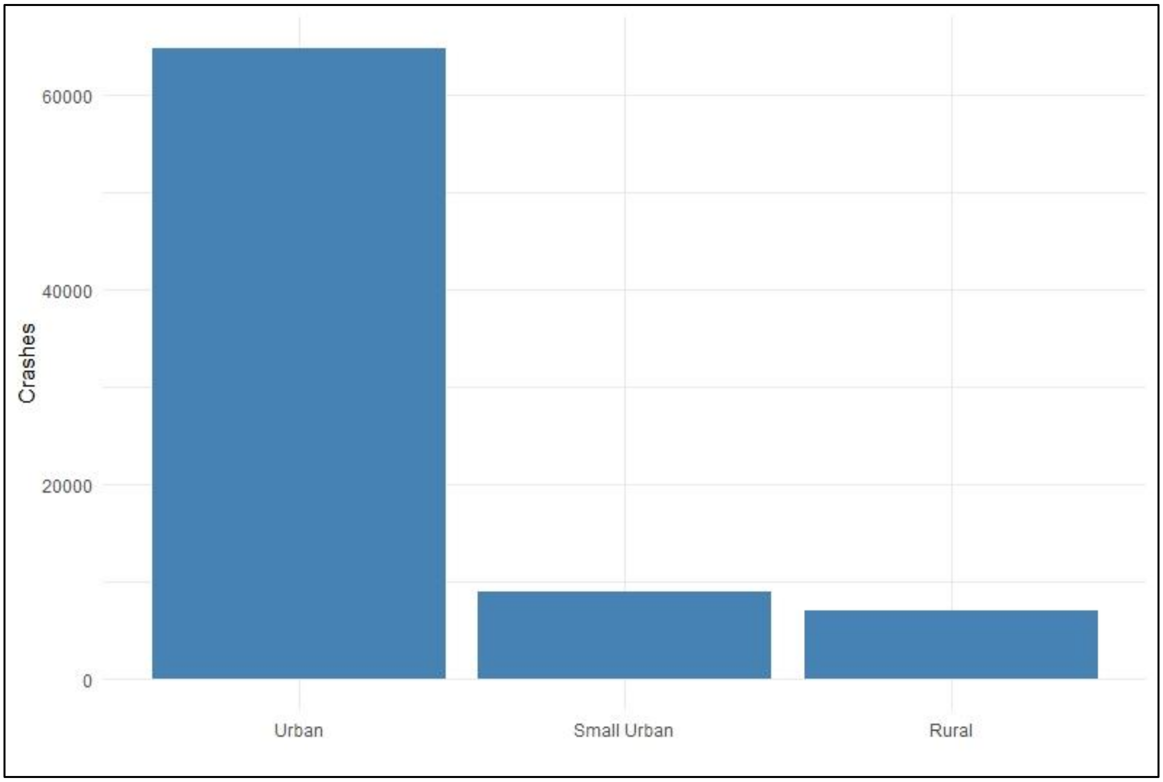

Figure 35. Bar chart. Crashes by land use type.

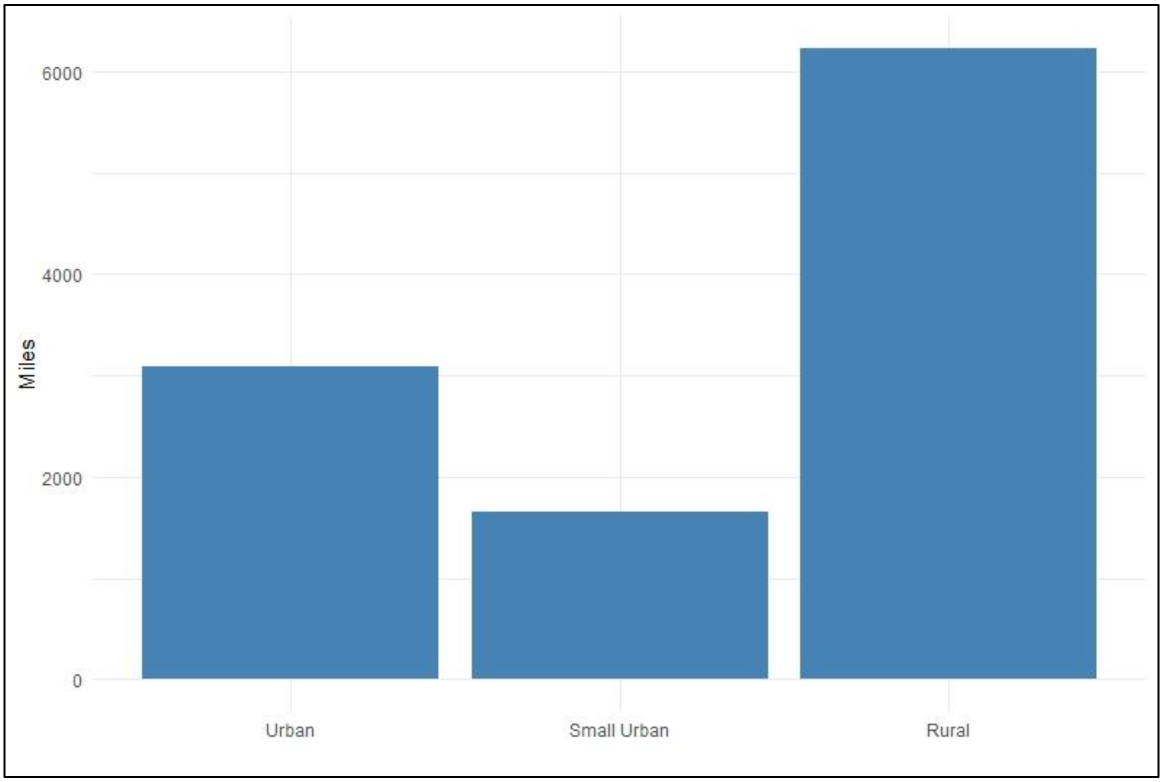

Figure 36. Bar chart. TMC mileage by land use type.

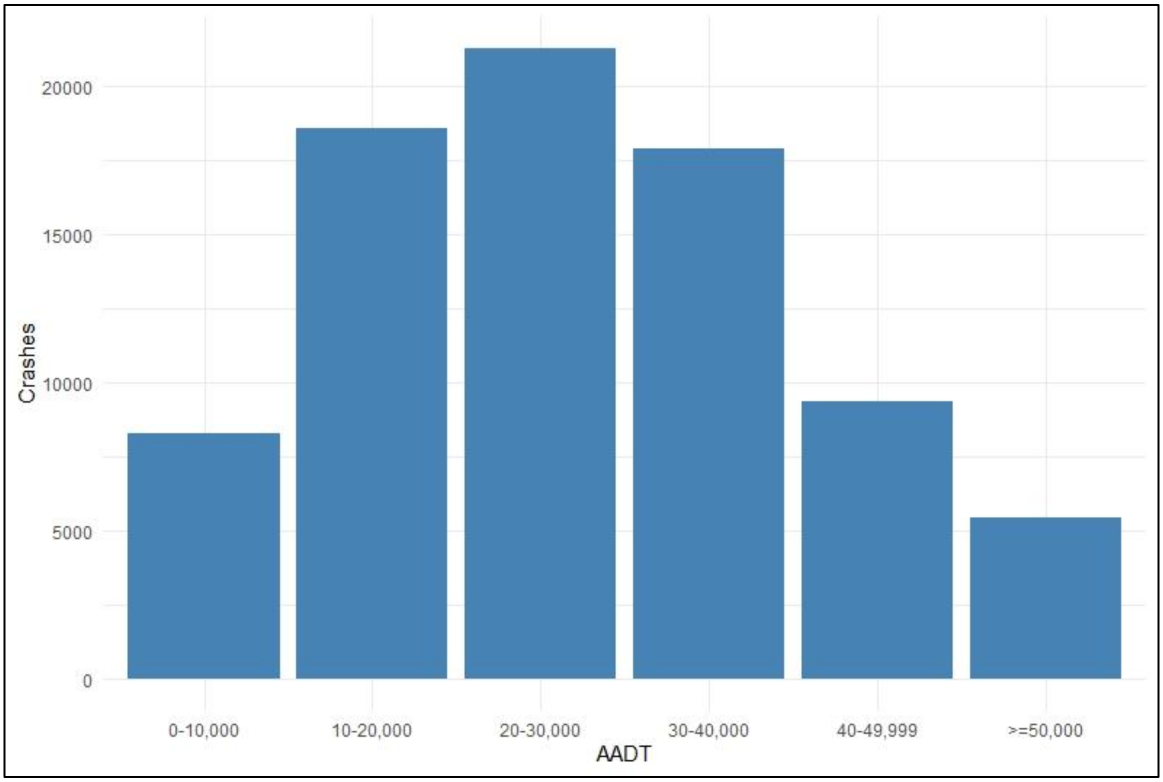

Figure 37. Bar chart. Crashes by AADT category.

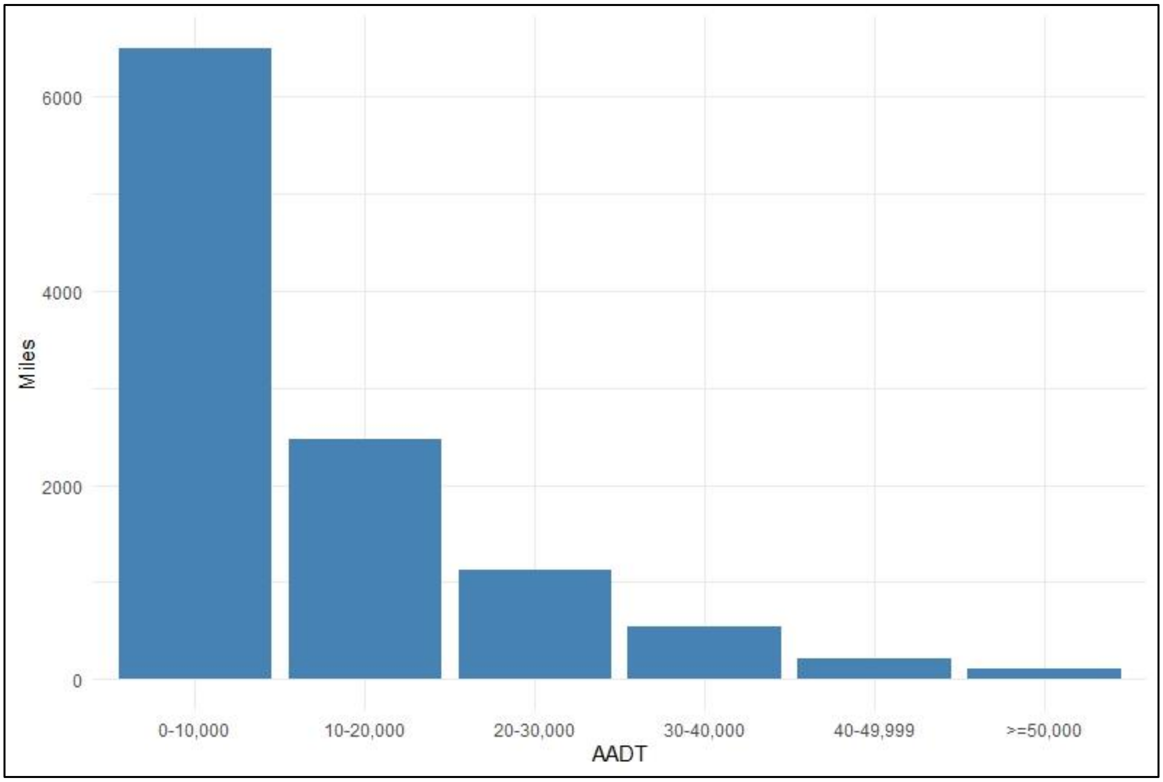

Figure 38. Bar chart. TMC mileage by AADT category.

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